Collaborating with Machines Rather than Commanding Them:

Interaction and Interface Design for a Human-AI Collaboration Paradigm

Clément Bordas

Collaborating with Machines Rather than Commanding Them:

Interaction and Interface Design for a Human-AI Collaboration Paradigm

Clément Bordas

Department of Graphic and Industrial Design
College of Design
North Carolina State University

May 9th, 2018
Submitted in partial fulfillment for the degree
of Master of Graphic Design

Helen Armstrong, *Chair*
Associate Professor of Graphic Design

Denise Gonzales Crisp, *Committee Member*
Professor of Graphic Design, Director of the Graduate Program in Graphic Design

Dr. Matthew Peterson, *Committee Member*
Assistant Professor of Graphic Design

Contents

CONTENTS

Preface

This book documents the final project of the Master of Graphic Design that marks the end of the degree but only the beginning of my research in this area. Artificial intelligence and machine learning advancements are accelerating across fields. While many applications of those technologies are being created, I focused on the interaction side. What will interacting with an artificial intelligence system be like? What new interactions will come out of human/machine relationships? How are those interactions going to transform the interface that visually translates those moments? These represent a small sample of the questions I considered while starting my investigation.

The book is divided into three chapters. Chapter One establishes the research space and the research involved in the project. Chapter Two looks at examples of artificial intelligence and machine learning systems but also sets the general framework for my investigation. Chapter 3 presents the design work that took place in response to my research question. The book then considers current research and potential ways to continue my exploration.

This project encourages the reader to think about our place in a society where artificial intelligence is expanding rapidly though numerous applications and forms. It provides a potential framework to help designers think about and design for such issues.

Acknowledgements

I would first like to thank my chair Helen Armstrong, Associate Professor of Graphic Design of the College of Design at North Carolina State University, who provided me great support and insights for my research and writing. This accomplishment would not have been possible without her.

I would also like to thank Denise Gonzales Crisp, Professor of Graphic Design, Director of the Graduate Program in Graphic Design, and Matthew Peterson, Assistant Professor of Graphic Design, both members of my committee who always were very inquisitive, bringing significant insights and challenges for me to address.

I’d like to thank Deborah Littlejohn, Assistant Professor of Graphic Design who helped me get this research started with the Final Project Preparation class from Fall 2017.

I’d like to thank all the faculty of the Master of Graphic Design as well as Tsai Lu Liu Department Head of Graphic Design and Industrial Design for having trusted me enough to offer me significant assistantship positions that granted me a great deal of teaching experiences to start a teaching career.

With immense gratitude, I wish to express my sincere thanks to my wonderfully supportive cohort and MGD students that I had the honor to work with.

Finally, I must express my very profound gratitude to my family—my mom, my dad and my two sisters—for providing me with unfailing support and continuous encouragement throughout my years of study across the ocean as well as to my boyfriend for his unconditional support and patience during those busy years of study.

Thank you.

ABSTRACT

Abstract

Progress made in artificial intelligence and machine learning is changing the way designers interact with computers. Machines are now able to transform billions of data points into insights, predictions and knowledge without the need for traditional programming. This information- and knowledge-abundant data enables computers to be trained to act as intelligent agents and is changing the relationship we have with the computer. These new technologies open up possibilities for reinventing user interface by applying interface and interaction design principles adapted to artificial intelligence and machine learning skills and to collaborative theories.

This research investigates the design of interfaces that utilize artificial intelligence and machine learning capabilities to help designers create design artifacts involving information-abundant research and dissemination. A framework, which integrates several Human-Computer Collaboration (HCC) approaches with artificial intelligence and machine learning, will underpin the design of these interfaces.

These interfaces visually translate opportunities for the development of a human-AI collaboration (HAC) paradigm, informed by theories of HCC but also design thinking. In this HAC paradigm, the human and the computer collaborate and contribute to achieve shared goals while considering the strengths and weaknesses of both partners. My research methods are based around this adapted HCC framework, mapping out a range of issues and themes using user journey maps, scenarios and storyboards, as well as the generation of visual studies and rapid prototyping.

Focusing this research specifically on the impact of artificial intelligence and machine learning upon collaborative activity, via an interface, forefronts the impact of big data upon the design process. To propose meaningful, inclusive design solutions, designers must be able to access and analyze expert data and knowledge. Machine learning techniques can enable designers to access this data and knowledge in real time and thus influence their design decisions. Ultimately, this research presents opportunities for designers to define a new relationship enabled by artificial intelligence.

Collaborating with Machines Rather than Commanding Them:

Interaction and Interface Design for a Human-AI Collaboration Paradigm

Chapter 1 - Introduction

“The actual path of a raindrop as it goes down the valley is unpredictable. We cannot see where it’s going. But the general direction is inevitable.” It is in these terms that Kevin Kelly, digital visionary and founding executive editor of Wired magazine, talked about the inevitability of a second industrial revolution during a TED talk in 2016. This second industrial revolution will establish a “cognification” (Kelly 2016) of our environment as technology becomes smarter via the explosion of artificial intelligence.

For many, this second revolution will come at a price. A 2016 report by the research and advisory firm Forrester estimated that by 2021, autonomous entities from artificial intelligence and cognitive technology “will have eliminated a net 6% of jobs” (*Forrester Predicts Iot, AI, AR, And VR Will Change The Tech World By 2021*). Another study from 2013 estimated that “about 47% of total US employment is at risk” (Frey and Osborne 1).

In this period of transition and uncertainty about a future profoundly impacted by artificial intelligence and its applications, we can either look at artificial intelligence as a technology that will replace human workers or look at artificial intelligence as a new space for opportunities that we could embrace and steer. Such conflicting approaches have happened several times in the past. For example, when the first Mac computer came out in 1984, designers felt that the computer and its applications were going to replace their jobs. However, designers such as April Greiman and the Design Type Foundry Emigre used the new to discover ways to express their creativity. Kelly stated that, “The most popular AI product 20 years from now that everyone uses has not been invented yet.” Danny Hillis asserts it is crucial that “we are remaking ourselves” and “choose wisely what we are to become” (Hillis) by engaging ourselves in this revolution. Kelly and Hillis emphasize the the importance of exploring this conversation.

1.1 Context and Conditions

The Brain's Last Stand

In 1997, IBM's supercomputer Deep Blue became the first computer to beat a reigning chess world champion, grandmaster — Garry Kasparov — in a tournament style game. The achievement was reported around the world and reanimated fears towards AI. The cover of Newsweek proclaimed the event, "The brain's last stand."

Despite sensationalization by the press, chess players and researchers actually expected that, with the evolution of technology, the computer would be able to beat a human player. Around the same time, David Levy a Scottish chess champion and friend of the father of artificial intelligence John McCarty, coined the term, "anti-computer tactics," to refer to the developments of tactics to give a human player more chances against a computer opponent. Such efforts reaffirmed the importance of human values and skills that are not replicable by the computer.

The Premise of Human-computer Collaboration

In 2005, eight years later, during a chess tournament, a pair of amateur American chess players using their own computers won the tournament against world grandmasters and well-known programs. This victory was the result of extensive work creating an exhaustive database of strategies addressing the immensity of possible situations. This victory, by a combination of human and computer chess players, is according to James Guszcza, Harvey Lewis and Peter Evans-Greenwood, "an excellent example of human-computer collaboration—and a cautionary tale about over-interpreting dramatic examples of computers outperforming humans" (17).

CHAPTER 1-INTRODUCTION × 1.1 CONTEXT AND CONDITIONS

Both the 1997 and 2005 victories were highly connected to humans. In 1997, those humans were the developers, engineers and expert chess players who developed the victorious program of the computer Deep Blue. In 2005, the humans were the two amateur chess players who engaged in this collaboration with their computers in which, "human strategic guidance combined with the tactical acuity of a computer was overwhelming" (Guszcza, Lewis and Evans-Greenwood 17). These humans created programs that effectively utilized grandmasters' game databases—also generated by humans. They used a traditional programming approach to articulate to the computer all the rules necessary to play chess.

A Change in The Game

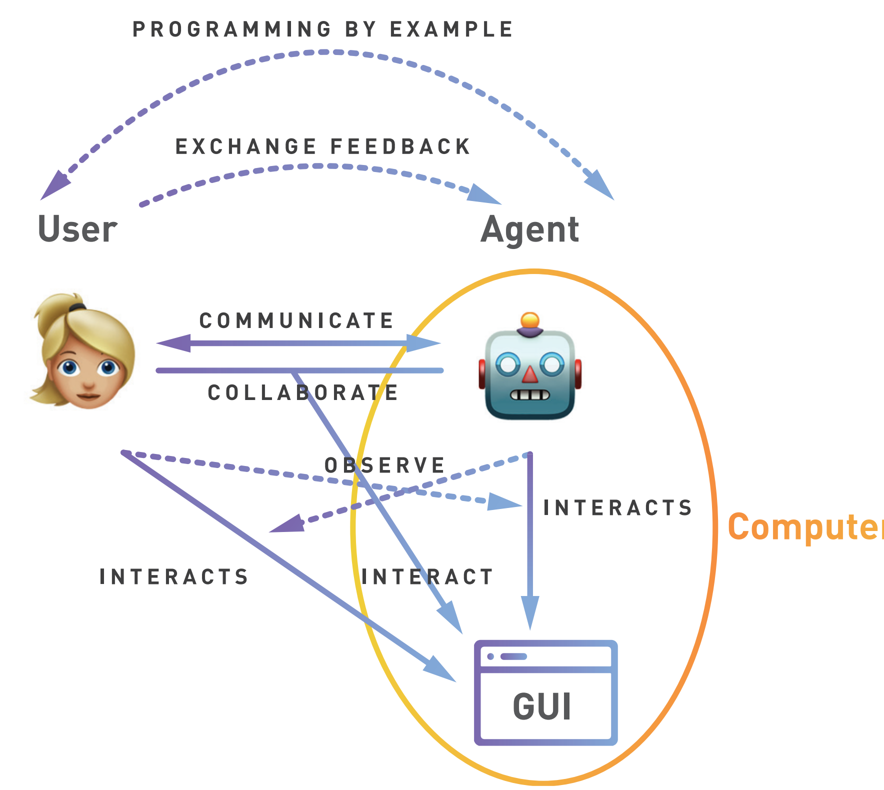
This rule-based programming approach changed radically with progress made in artificial intelligence (AI) and, more specifically, machine learning (ML). In 2015, Matthew Lai, a computer science student published a master's thesis that demonstrated a machine learning system that could learn to play at the International Master level of chess in just 72 hours. This student utilized a deep neural network—a ML system inspired by the structure of the brain that can learn and make decisions. This use of ML introduced decision-making based on predictive modeling. At no point the program is given specific instructions, rather the "AI algorithm sifts through otherwise unmanageable amounts of data to identify relevant predictions or recommendations" (Guszcza, Lewis and Evans-Greenwood 13) for the game and then take action.

The Collaborative Interface Agent

Today, humans are mainly left out of the fight to determine the best chess player as it has become an artificial intelligence fight, like with AlphaZero the latest game-playing AI. Progress in AI and ML are undergoing exponential growth and impacting our technical landscape profoundly. And while we acknowledge the power of artificial intelligence and the dangers that come with it, there are opportunities to look at AI as a useful partner via human-computer collaboration.

A collaborative interface agent is one example of a system establishing a context of collaboration between a user and a virtual agent. The collaborative interface agent is defined as “computer programs that employ machine learning techniques in order to provide assistance to a user dealing with a particular computer application” (Lashkari, Metral and Maes 1). Cheung also explains the collaborative interface agent is “able to communicate with and observe the actions of the human user” (13) and states that the relation between the user and the agent is similar to two humans collaborating to complete a task. The figure (fig. 1) below illustrates this definition of the collaborative interface agent.

Figure 1. Collaborative Interface Agent Paradigm Adapted from Gheung’s Model



ML growth has exploded since 2017. The potential to create applications informed by such a paradigm could change the image of a human-replacing technology.

The Current State of Machine Learning

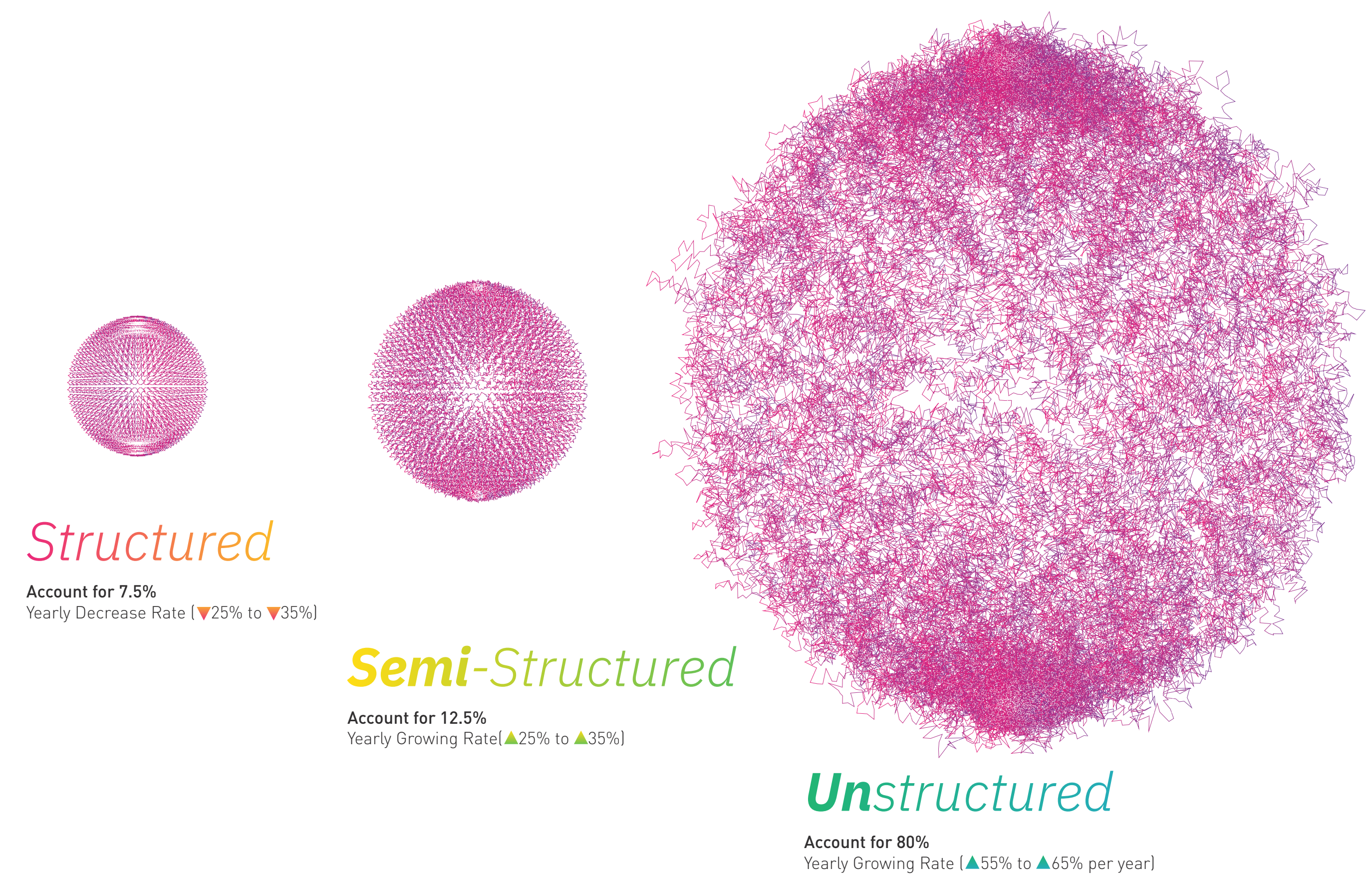
Machine learning, a subfield of AI, currently dominates the landscape of AI applications. ML algorithms transform billions of data points into insights, predictions and knowledge without the need for traditional programming. Traditional programming refers to the idea of logic-based programming in which the computer is explicitly instructed through a series of conditional steps. Using machine learning algorithms, a computer can perform actions and operations on its own based on generated evidence-based decisions. Current capabilities of machine learning include Natural Language Processing or the ability for the machine to understand words and sentences as humans do; image recognition, voice recognition, sentiment analysis and more. IBM Watson's products are well-known examples of what ML allows a computer to do.

Data is King

Data is the key element of machine learning — often referred to as data analytics or predictive statistics. We live in a world driven by data. More and more people have access to more and more tools generating more and more data. There are three kinds of data: (1) structured data is the data we can find in databases and spreadsheets, (2) semi-structured data is not formatted and organized as the structured data is but is still labeled and tagged in some ways allowing the content to be addressed. Such examples are XML documents and RSS feeds. Finally (3) unstructured data is all the content generated by web pages, e-mail, social networks, instant messaging apps, all the multimedia content such as documents, videos, photos uploaded on the web, etc..

In today's information era, "the data clearly signals a shift toward using more unstructured data sources" (Russom) (see fig. 2). This shift is due to our society where people are constantly generating data with their voices, their faces, their postures, their behaviors or their interactions with all the personal and public devices that we encounter on a daily basis.

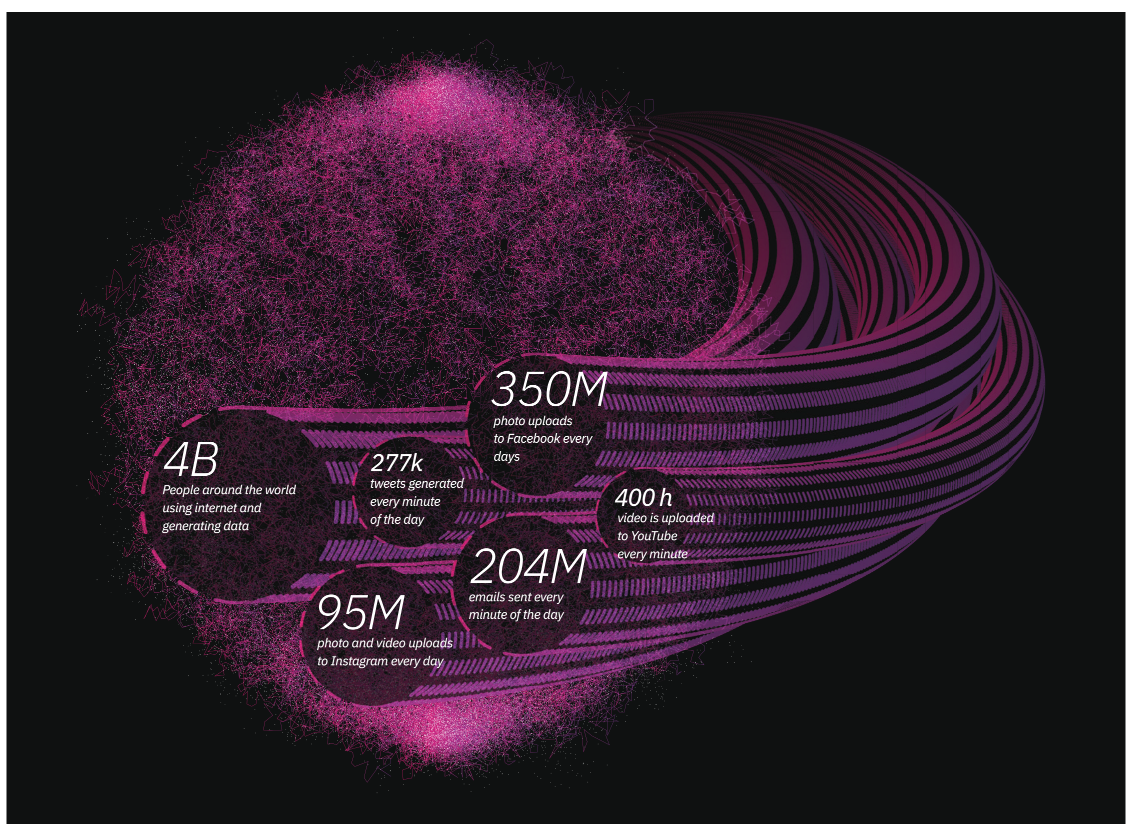
Figure 2. Data Landscape in 2018



The Problem

Humans can't keep up with the tons of data generated (see fig. 3) daily. It is becoming harder for users to access this data. Utilizing this data is, however, critical for personalized products and services. This suggests the need for a system that can parse massive amounts of data—i.e. machine learning. Such a ML system requires not only developers and engineers but also designers to design interfaces to support new interactions between user and AI.

Figure 3. Origins of Unstructured Data

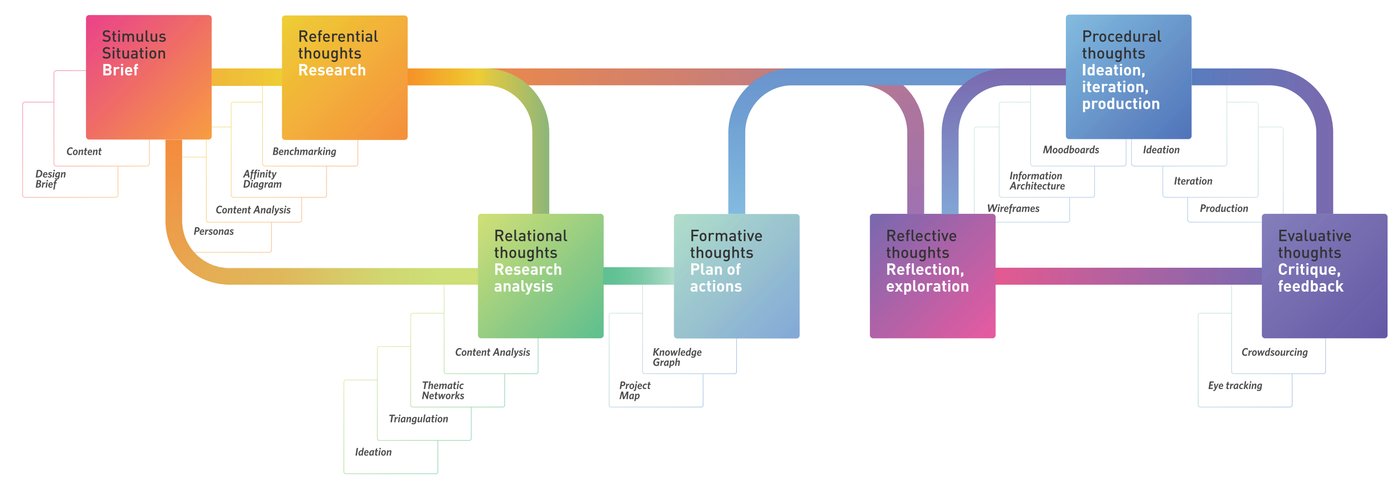


CHAPTER 1 - INTRODUCTION × 1.1 CONTEXT AND CONDITIONS

The Design Situation

Designers already deal with data as part of their research process (see fig. 4). Many research methods currently used by designers utilize data such as benchmarking, affinity diagramming, user research and personas, content analysis, thematic networks and so on. Designers thus need to create new interfaces that help them leverage this data via ML as part of their process.

Figure 4. Data Landscape in 2018



1.2 Research Questions, Subquestions and Definition of Terms

Research Question

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration, help designers create design artifacts that require information abundant research and dissemination?

Subquestions

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration,
...

Subquestion #1

...help designers access the value of data to improve their projects research and outcomes?

Subquestion #2

...help designers translate collaborative interactions into applicable knowledge?

Subquestion #3

...help designers integrate and synthesize knowledge into the project specifications and design making decisions?

Definition of Terms

Graphical User Interface

The Oxford Dictionary defines interface as "a visual way of interacting with a computer using items such as windows, icons, and menus, used by most modern operating systems" (*graphical user interface | Definition of graphical user interface in English by Oxford Dictionaries*). The first program to use a graphic user interface was Ivan Sutherland's 1963 program Sketchpad. The term interface has connections with ergonomics describing the site of interaction between the human and the computer or the "medium between human and machine to transmit information and is the specific form of expression between the human, machine, and environment, which is also the necessary means to realize the interaction" (Deng et al. 1).

Artificial Intelligence (AI)

Artificial intelligence is defined by the Oxford Dictionary as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" (*artificial intelligence | Definition of artificial intelligence in English by Oxford Dictionaries*).

Research Question

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration, help designers create design artifacts that require information abundant research and dissemination?

Definition of Terms

Machine Learning (ML)

Machine learning is defined by the Oxford Dictionary as "the capacity of a computer to learn from experience, i.e. to modify its processing on the basis of newly acquired information" (*machine learning | Definition of machine learning in English by Oxford Dictionaries*). Machine learning is an emerging condition coming from the application of artificial intelligence theory and developments, which allows the automation of systems through algorithms that learn from the data. The computers learn by analyzing and interpreting data without the need to be explicitly programmed. Machine learning is similar to predictive statistics. ML algorithms analyze huge quantities of data to make predictions.

Human-Computer Collaboration (HCC)

The study of human-computer collaboration (HCC) is highly interdisciplinary as "its two basic parent disciplines are artificial intelligence (AI) and human-computer interaction (HCI)" (Terveen 2). This interdisciplinary study involves aspects of collaboration defined as "a process in which two or more agents work together to achieve shared goals" (Terveen 2) in order to creatively solve problems and engage in project activities.

1.3 Justification

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities...

Artificial intelligence, specifically machine learning, is impacting the way people interact with computers. Utilizing machine learning capabilities creates a range of new interactions. Interfaces should support those new interactions in a way that complies with the situatedness of the users and their trust in the system. The designer has an important role in exploring these realms.

...in a context of use informed by human-computer collaboration,...

Human-computer collaboration theories offer themes and requirements to define a context of collaborative interactions. Insights from human-to-human collaboration widely informed in the development of those theories which is particularly relevant to a design practice for which the collaborative aspect is critical in today's practice.

...help designers create design artifacts that require information abundant research and dissemination?

Via machine learning, a computer can collect and process billions of data points to offer predictions and suggestions to the designer to consider in his/her work. An interface that utilizes machine learning, as informed by human-computer collaboration, could engage designers in critical discussions around how ML is impacting design practice and curricula. This investigation encourages the design community to re-define interactions with intelligent computers. Designers are at the forefront of making AI intelligible and accessible to ensure a shared understanding between the computer and its users.

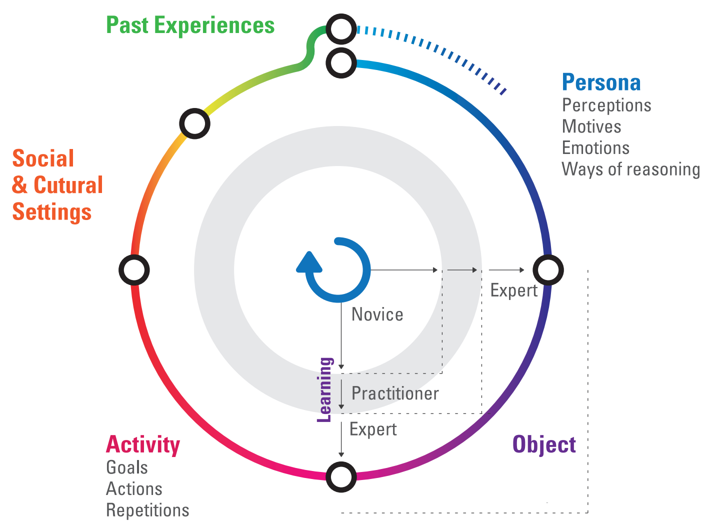
Addressing the need for a ML-powered interface will require that designers adopt more interdisciplinary methods of thinking. Designers will need to work closer with machine learning programmers, developers and data analysts. Those interdisciplinary collaborations will enable designers to embrace complexity in their design processes. Indeed, according to Patrick Hebron, "Engineers and designers are poised to approach ever more complex problems through machine learning. They will be able to produce more accurate results and iterate upon machine-learning-enhanced systems more quickly" (24).

1.4 Literature Review

Activity Theory

Activity theory looks at how people interact with technology by considering the fundamental activities engaged in the use of an object and influencing the surrounding environment (see fig. 5).

Figure 5. Activity Theory Cycle



In 2006, Kaptelinin and Nardi discussed the following components of the activity theory framework as visualized in the above figure:

- (1) People: people engaging with the object in response to their past experiences, perceptions, motives, emotions and way of reasoning.
- (2) Object: the object of interaction whom “characteristics result from and respond to the physical and technological affordances of the setting” (Davis 230).
- (3) Activities: “the means through which people, motivated to interact with their environment, accomplish something” (Davis 229).
- (4) Actions: “components of activities; ordered sequences of smaller events that constitute the complete activity” (Davis 229).
- (5) Operations: “actions that become routine through repetition and that are processed less consciously than other actions” (Davis 229).
- (6) Social and cultural setting: the context of interaction providing a richer framework that “matches how people actually use technology at work and play” (Kaptelinin and Nardi 6).

In the field of Human-Computer Interaction (HCI), activity theory is particularly meaningful as it provides a context to actions in order to be able to understand them. It also considers the historic and continuous development of the activity which is not static or rigid nor linear or straightforward.

The activity sets the context around various artifacts or objects which all have a mediating role. These objects are seen and manipulated within the limitations of the interaction imposed by the context (activity) and its elements (object, user).

Collaborative Interface Agent

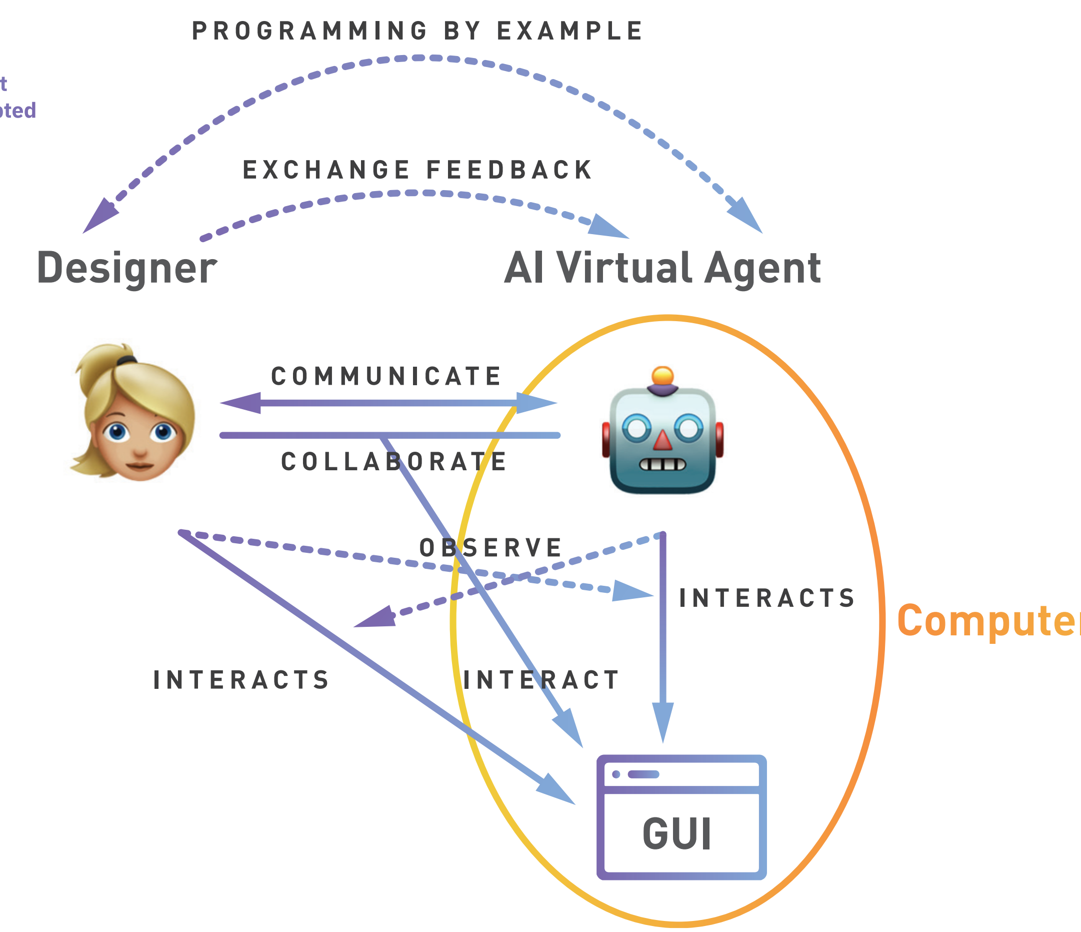
While activity theory allows us to set the context of interaction, the collaborative interface agent allows us to specify the nature of the object being used. The object considered in this research is a computer composed of a collaborative agent created from artificial intelligence and a GUI.

The collaborative interface agent is a computer program made with algorithms and employing machine learning techniques to actively assist the user with computer-based tasks. The collaborative agent behaves as a personal assistant who is collaborating with the user in the same work environment.

A collaborative interface agent is one example of a system establishing a context of collaboration between a user and a virtual agent. The collaborative interface agent is defined as "computer programs that employ machine learning techniques in order to provide assistance to a user dealing with a particular computer application" (Lashkari, Metral and Maes 1). Cheung also explains the collaborative interface agent is "able to communicate with and observe the actions of the human user" (13) and states that the relation between the user and the agent is similar to two humans collaborating to complete a task. The figure on the right (fig. 6) illustrates this definition of the collaborative interface agent.

CHAPTER 1 - INTRODUCTION × 1.4 LITERATURE REVIEW

Figure 6. Collaborative Interface Agent Paradigm Adapted from Gheung's Model



Collaboration and HCC Theories

What is Collaboration?

In 1996, Grosz provided an informal descriptive model of collaboration and proposed that collaboration must have the following three elements:

- (1) The participants must have commitment to the shared activity.
- (2) There must be a process for reaching an agreement on a recipe for the group action.
- (3) There must be a commitment to the constituent actions.

In 2000, Thomas Kvan defined collaboration as “a joint-problem solving, or working with others with shared goals for which the team attempt to find solutions that are satisfying to all concerned” (410). In this collaboration, he stated that the sense of working together is as important as achieving a holistic sense of active result. In such collaboration each participant is contributing in ways they can, bringing their domains of expertise to life in moments appropriate to the resolution of the shared problem.

CHAPTER 1 - INTRODUCTION × 1.4 LITERATURE REVIEW

Towards a Human-Computer Collaboration Framework

Several researchers (Terveen, Silverman, Calistri-Yeh) provide theories of human-computer collaboration (HCC) that introduce requirements and themes of a collaboration.

Loren G. Terveen, who defined collaboration as, “a process in which two or more agents work together to achieve shared goals” (1), considers the following fundamental issues that arise from her definition:

- (1) **Agreeing on the shared goal(s) to be achieved.** Through direct discussion about goals and inference from statements and actions, agents must determine the shared goals they are trying to achieve.

- (2) **Planning, allocation of responsibility, and coordination.** Agents must decide how to achieve their goals, determine what actions will be done by each agent, and how to coordinate the actions of individual agents and integrate their results.

- (3) **Shared context.** Agents must be able to track progress toward their goals. They must keep track of what has been achieved and what remains to be done. They must evaluate the effects of actions and determine whether an acceptable solution has been achieved.

- (4) **Communication.** Any collaboration requires communication, for example, to define goals, negotiate over how to proceed and who will do that, and evaluate progress and results. Observation of other agents also plays a role.

- (5) **Adaptation and learning.** Collaboration has a history, both short term — within a single session — and long term — across many sessions. True collaboration over time seems to require partners to adapt themselves to each other. Learning is one way to adapt. In a collaborative interaction, one can learn from one’s partner both directly, e.g., by being told or shown a new or better way of doing things, and indirectly, through the process of articulating, justifying, and explaining one’s actions and attitudes to a partner.

Barry G. Silverman who defined the term collaboration as referring to an idea of "mutual sharing of goals in completing the tasks" (166) provided the following collaboration factors:

- (1) **Cognitive orientation.** Cognitive orientation is the style of reasoning and dialogue the machine assumes. For example, if the human uses forward chaining to solve a problem, the machine might best support the user by looking at the problem via a different (e.g., backward chaining) perspective. Knowing when to assume a setting across this spectrum requires insight about the environment, organization, task, and user if the collaboration is to be successful.

- (2) **Deep knowledge.** It is an increasingly accepted premise of knowledge-based systems research that if (critiquing) systems are to enhance human performance successfully they must be given a deep understanding, an epistemological layer, from which to draw inferences about their domain of interest.

- (3) **Intention sharing.** Much of human-human collaboration appears to occur at the intention-sharing levels at which incomplete statements of goals, problem statements, plans, beliefs, and partial solutions may be explained and shared to clarify what actions are to be taken.

- (4) **Control plasticity.** In successful collaborations, the control in the dialogue and in the actions taken is joint and should be shifted back and forth throughout the session as a function of who is suggesting a more productive set of actions.

- (5) **Mutual and continuous adaptivity.** In the man-machine collaboration, the human should grow and learn about the domain from the strategies his or her problem-solving behavior precipitates. The machine, in turn, should become more knowledgeable as it is exposed to more cases.

CHAPTER 1 - INTRODUCTION × 1.4 LITERATURE REVIEW

- (6) **Remembering and analogizing.** Success in collaboration appears to increase with more experience between the collaborators. An important area addressed here is thus the long-lived, cross-case relationship between the machine and the collective factor due to its perceived importance to collaborative relationships.

Randall J. Calistri-Yeh defined collaboration as the following condition: "collaboration exists between two agents A and B if and only if:

- (1) A and B have mutual knowledge of a common goal g.

- (2) The goal g is decomposed into $g = g_a \cup g_b$ such that A agrees to be responsible for subgoals in g_A and B agrees to be responsible for subgoals in g_B.

- (3) Both A and B make a significant contribution toward the solution of g.

- (4) There is an opportunity for communication between A and B.

- (5) The combined contributions from A and B have a synergistic effect on the solution of g (or on the solution of a higher-level goal of one of the agents).

- (6) Some part of A's contribution temporally meets or overlaps some part of B's contribution" (5-6).

He expanded on those requirements as follow:

- (1) **Common goal.** This requirement simply says that both A and B share the same goal, and that both of them know that they are sharing the same goal. Requiring a common goal is obvious; requiring mutual knowledge of the goal eliminates cases of independent researchers who coincidentally share the same goal.

- (2) **Goal decomposition.** This requirement serves two purposes. First, it guarantees that all parts of the goal are covered during task allocation. Second, in conjunction with the common goal requirement it guarantees that some amount of cooperation is taking place: once both agents agree to the common goal and the decomposition, there is intentional joint action.

- (3) **Dual contributions.** Each agent must make a significant contribution. Note that the definition does not require that the common goal actually be achieved: collaboration may end in failure.

- (4) **Communication.** This requirement does not actually require that any explicit communication take place between A and B, only that the potential exists. But that potential itself may constitute implicit communication.

- (5) **Synergy.** This requirement represents the work of both agents contributing to the collaboration by working either on their planified tasks or the opportunistic actions appearing during the process.

- (6) **Timing.** The intuition behind this requirement is that the two agents should be working together on the task at the same time or by alternance where both agents would stay involved.

CHAPTER 1 - INTRODUCTION × 1.4 LITERATURE REVIEW

While Calistri-Yeh didn't include knowledge as one of the requirements, he asserted that knowledge is required and needed for any collaboration and that this knowledge is accessible through different sources that he listed as:

- (1) A model of the domain; precisely the domain of the investigation,

- (2) A model of the user's goals,

- (3) A model of the user's plans,

- (4) A model of the system's and the user's aptitudes to ensure the best task allocation,

- (5) A model of the user's knowledge for the system to provide tailored explanation.

The model of the domain and of the user's goals are required to attempt any collaboration.

CHAPTER 1 - INTRODUCTION × 1.4 LITERATURE REVIEW

Attempted Framework of Human-Computer Collaboration

Terveen, Silverman and Calistri-Yeh share some common ground in their theories of human-computer collaboration, but they differ when it comes to the knowledge required during the collaboration and the dynamic of the relationship between designer and intelligent computer.

I created a framework (see fig. 7) of human-computer collaboration adapted from Terveen, Silverman and Calistri-Yeh theories as well as the unified approach attempted by Terveen. The final framework presents the seven themes of human-computer collaboration that will inform the design of the interface and interactions between the design and the intelligent computer.

Figure 7. Human-Computer Collaboration Framework

HUMAN-COMPUTER COLLABORATION THEORIES			ATTEMPTED FRAMEWORK OF HCC ADAPTED FROM CALISTRI-YEH, SILVERMAN AND TERVEEN THEORIES
Human-Computer Collaboration Requirements (Calisti-Yeh)	Man-Machine Collaboration Factors (Silverman)	Human-Computer Collaboration Issues (Terveen)	Themes of Human-Computer Collaboration Based and Adapted from Terveen's Unified Approach (Terveen)
Common Goal	Intention Sharing	Determining Share Goals	*Shared Intent and Intent Specifications*
Goal Decomposition	Control Plasticity	Allocating Responsibility, Planning and Coord.	*Joint Cognitive System*
.	.	Shared Context	*Reification*
Communication	.	Communication	*Natural Communication*
Synergy	Cognitive Orientation	.	*Balancing Representation & Reasoning, and Interaction*
Dual Contributions, Timing	Mutual and Continuous Adaptivity	Adaptation and Learning	*Collaborative Adaptation*
Knowledge	Deep Knowledge	.	*Knowledge*

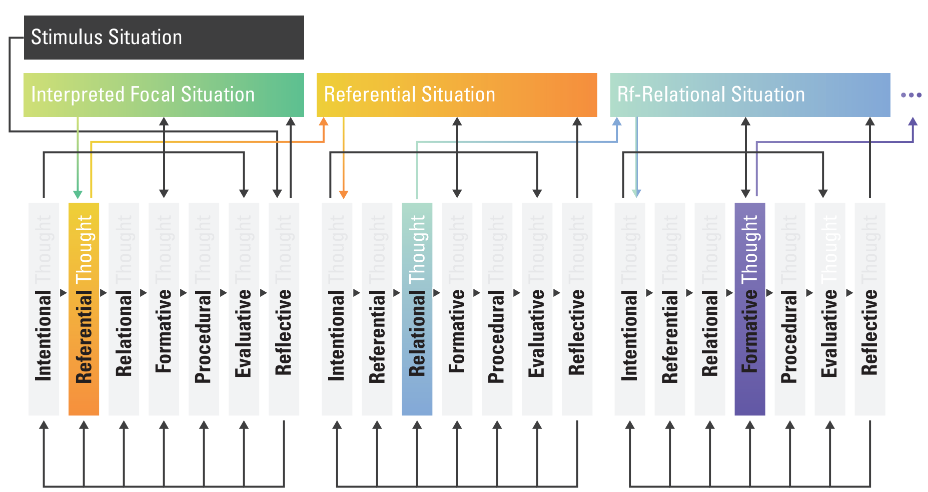
Design Thinking Theory

Design thinking is moving away from a linear process toward a succession of discrete steps with a specific focus on allowing exploration and divergence. Charles Burnette's theory of design thinking is especially relevant in regard to the non-linearity within the process. Burnette came up with the following list of seven thinking modes:

- (1) **Intentional Mode.** Executive thought to manage the resolution of a need or desire – i.e. to cross the street.
- (2) **Referential Mode.** Nominal thought to identify and define discrete objects and actions that have relevance to your need in the situation – i.e. Status of light, traffic, distances, etc.
- (3) **Relational Mode.** Associative thought to structure and analyze the Referential information to fit the problematic situation and your intention regarding it – model alternative crossing options and select one.
- (4) **Formative Mode.** Synthesizing thought to express and communicate a plan of action, the meaning of the situation, its subject or anticipated outcome. – Commit to a crossing plan and its probable outcome.
- (5) **Procedural Mode.** Productive thought to execute sequential actions to carry out a plan or change an expression or situation – execute the crossing.
- (6) **Evaluative Mode.** Comparative thought to assess a procedural outcome against some standard or expectation – assesses performance and result.
- (7) **Reflective Thought.** Proactive thought to learn from the experience and apply the experiential knowledge – incorporate what you've learned into what you know.

The figure below (fig. 8) represents the beginning of a design activity employing this design thinking theory. We can identify the point of entry of the project as the “Stimulus Situation.” The activity then moves to an interpretation of the situation, becoming a reference for the project from which we can create connections within its elements, and so on. At every moment of the design situation, Burnette’s theory of design thinking is representing the nonlinearity of the design process by allowing each mode of thinking to be used in combination of others and in a non-defined order.

Figure 8. Burnette’s Theory of Design Thinking in Action



This non-linear design thinking is especially relevant to collaboration in which agents are contributing what they can in different domains of expertise at moments when they have knowledge appropriate to the situation.

Kvan, who wrote about collaboration and design collaboration, also agrees with this idea of non-linearity of the design thinking process and said that, “The design moves in discrete steps, perhaps not linearly [...] but still in ways that we can see a step and identify what has happened during that step” (411).

Artificial Intelligence and Machine Learning

Current artificial intelligence and machine learning allows us to access insights and patterns from information-rich databases and create metadata. To access this data, the agent has skills ranging from natural language processing to generating evidence-based predictions, allowing the development of new kinds of interactions between the user and the computer through an interface informed by these skills.

Designers can explore how to visually translate the agent’s skills to make the AI’s reasoning accessible and demystified while allowing the designer to increase his/her trust in the system and situatedness in the partnership.

Interface Design Considerations

Information Visualization

Information visualization (information architecture and visualization of complex data) is a critical issue when designing for artificial intelligence and machine learning applications, as machine learning is directly related to the field of data analytics.

Interface Structure and Interaction Design

The structure (layout) and the interaction (navigation, actions, commands, inputs, feedbacks) of such interfaces require that they are dynamic as they are supposed to mimic a collaborative activity in which the discourse is never linear and templated. This interface needs to allow information sharing, communication, progress management, as well as explorations of the space.

Challenge of creating an interface that supports creativity and collaboration

Visualizing data and processes is crucial in this human-AI collaboration paradigm to support problem-solving tasks and creative exploration. Ben Shneiderman suggests that, “by placing known information in an orderly compact structure they support users in solving problems, planning activities, and making further discoveries” (4) and defines information visualization as “a compact graphical presentation and user interface for rapidly manipulating large number of items (10^2-10^6), possibly extracted from larger datasets. Effective information visualizations enable users to make discoveries, decisions, or explanations about patterns (correlations, clusters, gaps, outliers,...), groups of items, decisions, or individual items” (5).

“Information visualization supports creative work by enabling users to:

- (1) Find relevant information resources in digital libraries,
- (2) Identify desired items in a set, or
- (3) Discover patterns in a collection.” (6-7)

1.5 Assumptions

Designers use computers daily. Computers are critical to design practice. Computers and software have always been subject to updates and changes. While most of the updates do not require huge adaptation from the user, AI and machine learning applications are starting to generate new types of interactions between the human and the computer requiring new kind of behaviors.

For this research, I’m building upon current skills and applications in AI and machine learning to create a range of interactions between the designer and the AI agent that will enable collaboration within moments of the design thinking process. Using the data analytic capabilities of the AI agent will also transform design software from production only tools to tools that support both production and research. In addition to learning new features, designers will have to change how they think about the computer to begin contributing to this new relationship with the AI agent, beyond a human-operator relationship.

I am making the assumption for my research that the system the designer is working with has already been trained. Therefore, the interactions considered in my prototypes demonstrate interactions between a trained AI and a designer, in which the only teaching is coming from the experiences themselves that keep developing or particularizing the AI knowledge.

1.6 Limitations

While defining what this investigation encompasses, it is necessary to make clear the limits of this investigation.

Artificial intelligence and machine learning are both fields of research of their own, and it is important to draw the limitations of how I am using these two fields of study in my research. As stated earlier, I am looking at AI and machine learning through the lens of their current uses and applications in the market rather than through computer engineering.

Human-Computer Collaboration theories provide this research with themes and criteria to identify moments in which an AI agent and a designer could collaborate. These theories have allowed me to establish a framework of action in my investigation and informed my design making in the prototyping phase of the research. Through this research I also attempt to identify whether or not a designer working with an AI agent can be considered collaboration.

The investigation acknowledges that the design field is transitioning and thus, while many design thinking theories are out there, I am considering a theory that reinforces a non-linear process.

This investigation does not aim to establish universal, formal principles for the design of interfaces utilizing AI and machine learning applications, but rather it explores and speculates about the inclusion of such technologies into the designer's digital work environment in moments that are meaningful to his/her design process.

CHAPTER 1 - INTRODUCTION × 1.6 LIMITATIONS

Benefits of designers working with machine learning

- (1) Giving users/designers access to algorithm's data set, so that they can make informed decisions about technology that increasingly shape their lives.

- (2) Allow designers to create "personalized products and services that meet people's needs and guide them to discover and explore the world in ways they couldn't do without technology" (Stringer).

Chapter 2 - Research
2.1 Precedents

The precedents examined here are digital products and services putting in use current machine learning applications that grew out of the field of artificial intelligence.

Included are examples that: (1) facilitate conversations; (2) enable multimodal user inputs; (3) analyze abundant and complex information; (4) support creativity; and (5) facilitate collaborative interactions.

2.1.1 Facilitating Conversations

AI assistants, also called virtual assistants, are programs that converse and complete tasks for users using natural language understanding. AI assistants can be invoked by pressing a physical button (Figure 9), through text (Figure 10) or voice-activated (Figure 11) - Apple's Siri, Amazon's Alexa, Google Assistant) using voice recognition to reply to a specific user only (Figure 12).

Figure 9. Invoking Siri on the iPhone X Using the Side Button

How-to-Activate-Siri-on-IPhone-X. Jpg 700×555 Pixels. https://cdn.igeeksblog.com/wp-content/uploads/2017/09/How-to-Activate-Siri-on-iPhone-X.jpg. Accessed 8 May 2018.

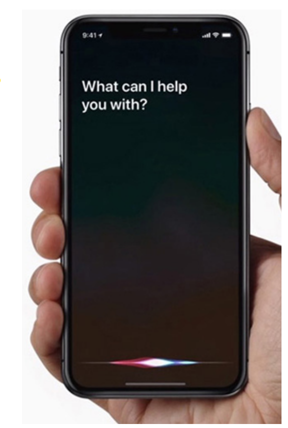


Figure 10. Invoking Google Assistant through Text

Google-Assistant-Text-Input.Jpg 1,200×1,067 Pixels. https://cloud.addictivetips.com/wp-content/uploads/2017/05/google-assistant-text-input.jpg. Accessed 8 May 2018.

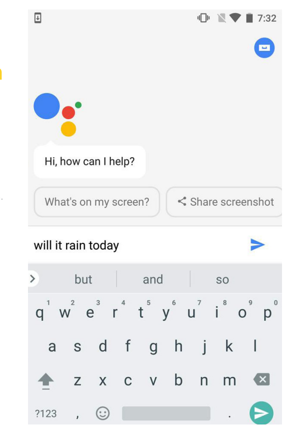


Figure 11. Invoking Siri by Voice

iPhone X

Figure 12. Configuring "Hey Siri"

iPhone X

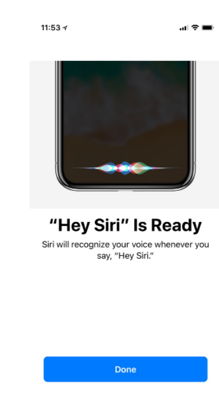
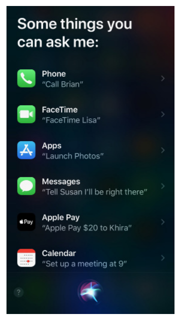


Figure 13.
“Hey Siri, what can you do?”

iPhone X

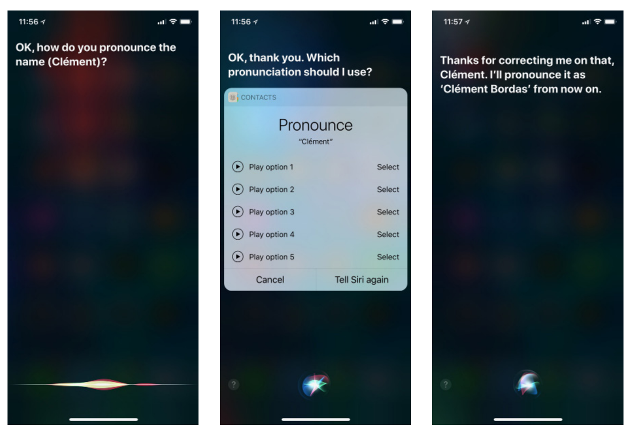


AI assistants also have knowledge discovery capabilities to provide users information, suggestions or actions to be taken (Figure 13). In that realm, Google Assistant has the benefit of being powered by the world’s largest search engine.

While most of these AI assistants are not designed to be taught directly except for minimal interventions (Figure 14), they do learn more about their users by analyzing their data and behaviors to create accurate and tailored interactions. This latter process is referring to as the mining of the user’s personal data.

Figure 14.
“Hey Siri, learn to pronounce Clément”

iPhone X



AI assistants are multiplying quickly and becoming part of today’s technological landscape. They are getting available through a variety of platforms and devices from smartphones, to speakers, watches, laptops, TVs, cars and smart displays.

Some AI assistants are designed for more specialized interactions. For example, some are purely designed to be conversational like Replika (Figure 15) in the attempt to create a friend-like relationship; some are purely designed to help a user complete a specific task (Figure 16).

Figure 15.
Replika in iOS

iPhone X
Mezi.Png 300×612 Pixels. https://beta.techcrunch.com/wp-content/uploads/2015/12/mezi.png. Accessed 8 May 2018.

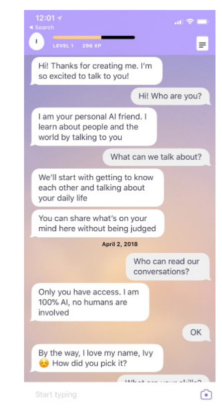
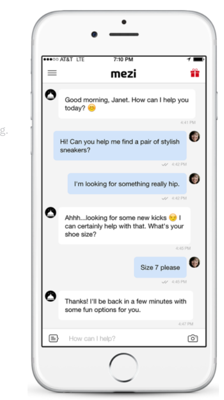


Figure 16.
Mezi

Mezi.Png 300×612 Pixels. https://beta.techcrunch.com/wp-content/uploads/2015/12/mezi.png. Accessed 8 May 2018.



A wide range of specialized agents exists and cover many specific uses in areas such as personal use, health, entertainment, finance, sport, education and so on.

2.1.2 Enabling Multimodal User Inputs

“It is gestures, smiles and frowns that turn a conversation into a dialogue”

(Negroponte 11)

Machine learning capabilities such as voice recognition, image recognition, facial expression recognition, and gesture recognition enable users to go beyond the limitations of traditional input devices such as the keyboard and mouse. As machine learning, “continues to make a wider variety of media understandable to computers, designers should begin to employ ‘multimodal’ forms of human-computer interaction, allowing users to convey ideas through the optimal means of communication” (Hebron 25).

Numerous products and applications are already taking advantage of these capabilities. NUIA is a software that allow users to use their voice, gestures and their gaze to control their computer. The software is enabling new inputs on compatible current applications and programs.

While NUIA uses multimodal user inputs for navigation, others utilize the analytic side of multimodal input. For example, the company eyeSight offers the expertise of computer vision and deep learning solutions thus providing viewers with analytic data. The company utilizes visual recognition, presence detection, head motion detection, eyelid and iris tracking, facial recognition, gender and emotion recognition and gesture recognition capabilities to enable real-time insights as well as content personalization.

These multimodal inputs capabilities are generating new ways for users and designers to interact with their computer beyond the keyboard and the mouse. In addition to machine learning enabling computers to understand and recognize more and more media, computers are becoming an extension of those media rather than a simple replication. This extension enhances the interactions that are happening, becoming meaningful and using this understanding to generate data.

CHAPTER 2-RESEARCH × 2.1 PRECEDENTS × 2.1.2 ENABLING MULTIMODAL USER INPUTS

2.1.3 Analysing Abundant and Complex Information

Machine learning enables humans to access an increasing amount of data in a tailored and meaningful way.

Here are some examples of services leveraging data.

VoiceBase
Voicebase.com

The company VoiceBase provides speech analytics solutions to help companies leverage patterns and data not recognizable to the human eye. Using natural language understanding, speech-to-text and knowledge extraction and analysis capabilities, VoiceBase detects complex events in their customers' databases as well as predicts the likelihood of future behaviors.

Text Metadata Services group
Clearforest.com

The Text Metadata Services (TMS) group from the company Thomson Reuters employs artificial intelligence and machine learning technologies to extract information and allow question answering by looking at a large corpus of documents. The extracted information consists of metadata, or data about the data, and linked data. This information is presented through a visualization of this knowledge.

Google's Knowledge Graph
Google.com

In 2011, Google introduced The Knowledge Graph or a visual conceptualization of what is happening behind the scene when searching the search engine. The Knowledge Graph references how natural language understanding and knowledge discovery capabilities are being used throughout a search. While The Knowledge Graph was more used as a marketing tool for Google's search engine, it shows the relevance of the visualization of concepts and processes to explain the impact of machine learning capabilities on our daily interactions.

2.1.4 Supporting Creativity

AutoDraw
Autodraw.com

Google also leads a multitude of research projects exploring the role of machine learning in the process of creating art and music. One of these projects is AutoDraw, a new kind of drawing tool that pairs the visual recognition capabilities of machine learning with drawings from artists. As the user starts drawing, AutoDraw matches the users' doodles with a list of drawings that look like the one being drawn.

Magenta
Magenta.tensorflow.org

Magenta, another research project by Google, developes new learning algorithms for generating songs. Magenta uses machine learning to generate compelling music. Similar to that project, Feynman Liang created a research project called BachBot at the University of Cambridge to train an artificial intelligence to learn and generate harmonized chorales indistinguishable from Bach's own work.

2.1.5 Supporting Collaborative Interactions

InVision, a design prototyping software, has recently implemented more collaborative attributes. Designers can now communicate through annotating features that allow users to directly input comments within the design canvas itself.

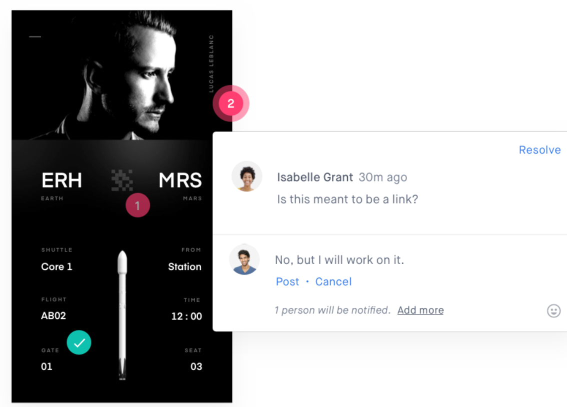


Figure 17. Seamless Design Communication in InVision

Demo-Comment.Png 1,200×864 Pixels. https://s3.amazonaws.com/www.invisionapp.com/static/projects/home/demo-comment.png. Accessed 8 May 2018.

The software also facilitates the design development workflow by allowing users to create and share stylesheets, get pixel-perfect comps, discuss design challenges, export adaptively, and generate real code for any design elements when needed.

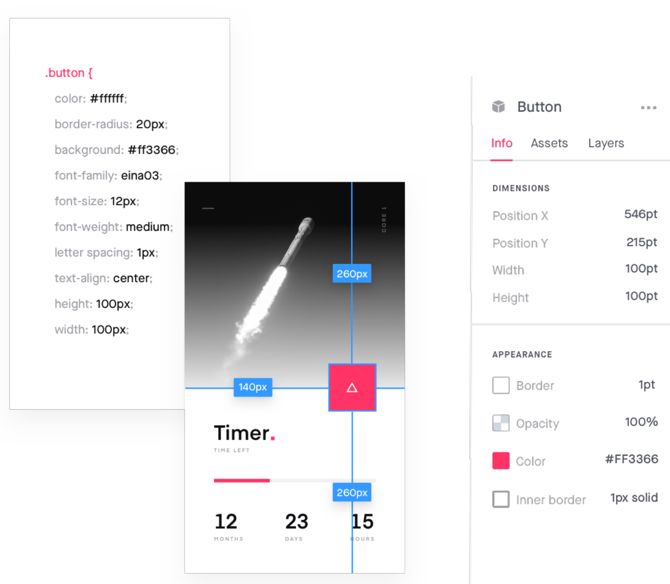


Figure 18. Use of Stylesheet in InVision

Demo-Inspect.Png 1,202×1,086 Pixels. https://s3.amazonaws.com/www.invisionapp.com/static/projects/home/demo-inspect.png. Accessed 8 May 2018.

Invision implemented more flexible board capabilities. Users can create custom boards to develop their moodboards, brand boards, image galleries, lo-fi prototypes, final design assets and so on.

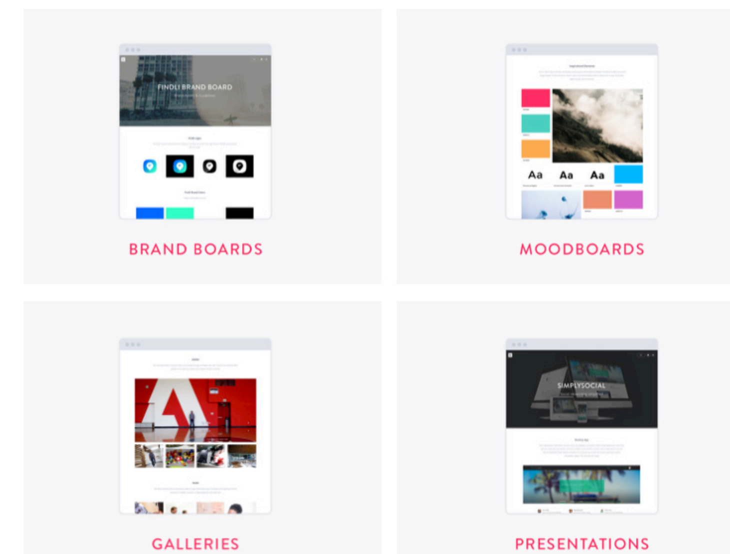


Figure 19. Boards in InVision

Brandboards.Png 790×590 Pixels. http://s3.amazonaws.com/blog.invisionapp.com/uploads/2015/08/brandboards.png?ver=1. Accessed 8 May 2018.

Recently, InVision created a collaborative add-on to their software called Freehand. Freehand is intended to bring design teams together to collaborate more efficiently on a common project. With Freehand, users are able to sketch, draw, wireframe, share feedback, present designs and make quick intuitive changes in real time.

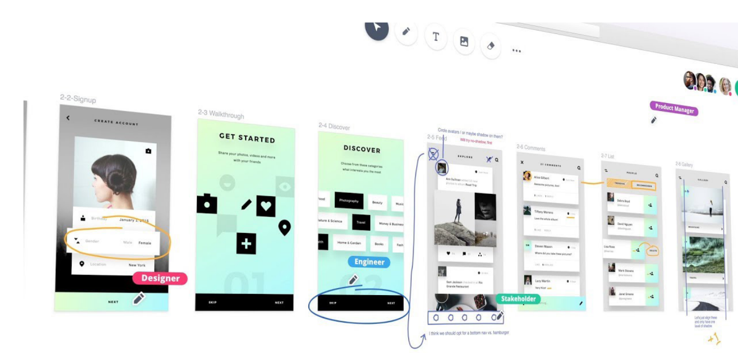


Figure 20. Freehand Feature in InVision

Maxresdefault.Jpg 1,280×720 Pixels. https://i.ytimg.com/vi/zd65qDvLZF0/maxresdefault.jpg. Accessed 8 May 2018.

Finally, InVision, a design-driven project management software, allows users to quickly access and share the progress made on their projects through project screens and statuses, progress or inquiry notifications and preview screens.

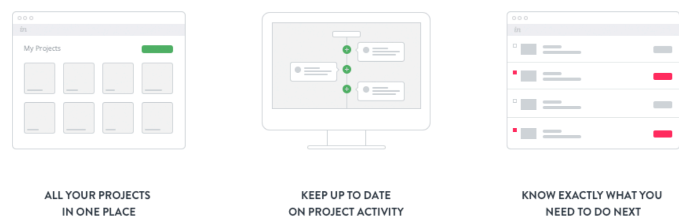


Figure 21. Project Management and Worflow for Designers

Mockup-Workflow.Png 1,138×669 Pixels. https://www.invisionapp.com/assets/img/home/animations/new/mockup-workflow.png. Accessed 8 May 2018.

Whiteboard
Products.office.com

The companies producing other software, like Microsoft Whiteboard, are also trying to create tools to enable more intuitive process work when designers collaboratively develope a concept with a moodboards and sketches. (Link aside - Whiteboard - https://products.office.com/en-us/microsoft-whiteboard/digital-whiteboard-app)

Coggle
Coggle.it

Mind mapping tools like Coggle allow users to manipulate text and images, while constructing meaningful connections and relationships between concepts and entities.

2.1.6 Takeaways

Facilitating Conversations

Conversational applications—made possible by machine learning—enable goal oriented conversations to answer users' needs by mining personal data. Available on several platforms, they utilize data stored and shared on the cloud. Conversational interfaces democratize how users interact with their computers.

Enabling Multimodal User Inputs

As computers recognize and understand more and more forms of media, users will be able to interact with computers in ways beyond using the keyboard and the mouse. Designers can think how sketches might be recognized by the computer, how video interviews and observational studies might be processed and analysed more easily, how user testing could have instantaneous repercussions as the user goes through testing, and how the computer might process images in a wink-of-an-eye.

Analysing Abundant and Complex Information

Machine learning creates multiple opportunities for designers to leverage data. In one hand, the data gathered provides insights for the creation or development of services. On the other hand, the interactions with those services generate insights into current uses of the services but also predicts how behavior might evolve over time. This informs how services should be updated and improved. Data can be leveraged by designers at the forefront and the background of any services.

Visualizations can address the complexity of such large datasets, making the data accessible to wider audiences beyond data specialists.

Supporting creativity

More applications use machine learning to support users' creativity. The appearance of these applications attests to the system's involvement in creativity. One could question whether or not the system is itself creative or is just providing another tool for designers.

The creativity behind machine learning resembles more randomized appropriation and exponential variations, rather than pure creativity and intuition. To support this idea, in 2016, Field, a creative studio based in London, created a digital 3D structure with the help of an algorithm, rendering over 10,000 images of this structure from various angles and vantage points.

Supporting collaborative interactions

Digital collaborative space needs to mimic the affordances of a collaborative physical environment. Human-to-human collaboration in a physical environment involves a wide range of media, tools, and resources. Dynamic digital interface could reflect such back and forth interactions and an ongoing particularization of the project. The idea of time is also fundamental and suggests the need for accessing the history of such collaboration.

2.2 Case Studies
2.2.1 AI and Machine Learning Research

2.2.1.1 IBM Research

IBM Research has been exploring artificial intelligence and machine learning technologies for decades. IBM researchers believe that AI will transform the world in dramatic ways in the coming years. IBM Watson is a system utilizing artificial intelligence to ingest, enrich and normalize a wide variety of data types without any additional integration, allowing users to leverage data from a broad range of sources with ease. IBM Watson can help users accelerate the discovery of meaningful information, enrich user interactions with technologies, and recommend actions with confidence based on evidence.

Conversation Integrate diverse conversation technology into your application.	**Chatbots** **Watson Assistant** **AI Assistants**
Data Embed AI, machine learning and deep learning to drive insights from data, wherever it resides.	**Watson Studio** Build and train AI models, and prepare and analyze data, all in one integrated environment. **Watson Machine Learning** Use your data to create, train, and deploy self-learning models. Leverage an automated, collaborative workflow to build intelligent applications. **Watson Knowledge Catalog** Intelligent data and analytic asset discovery, cataloging and governance to fuel AI apps.
Knowledge Get insights through accelerated data optimization capabilities.	**Discovery** Unlock hidden value in data to find answers, monitor trends and surface patterns. **Discovery News** Access pre-enriched news content in real-time. **Natural Language Understanding** Natural language processing for advanced text analysis. **Knowledge Studio** Teach Watson to discover meaningful insights in unstructured text.
Vision Identify and tag content then analyze and extract detailed information found in an image.	**Visual Recognition** Tag and classify visual content using machine learning.
Speech Convert text and speech with the ability to customize models.	**Speech to Text** Easily convert audio and voice into written text. **Text to Speech** Convert written text into natural-sounding audio.
Language Analyze text and extract meta-data from unstructured content.	**Language Translator** Translate text from one language to another. **Natural Language Classifier** Interpret and classify natural language with confidence.
Empathy Understand tone, personality, and emotional state.	**Personality Insights** Predict personality characteristics through text. **Tone Analyzer** Understand emotions and communication style in text.

Figure 22. Table of IBM Watson Applications

IBM Watson
Ibm.com/watson/

2.2.1.2 People + AI Research (Pair) Initiative

People + AI Research
ai.google/pair

People + AI Research (PAIR) is a Google initiative that improves how humans and AI interact while focusing on the human-side of this Human-AI relationship. PAIR is the first cross Google initiative to bring design thinking and human-computer interaction to machine learning.

The initiative provides resources and open-source material and tools for users to learn about and experiment with artificial intelligence and machine learning, as well as a collection of essays authored by designers working at Google.

Teachable Machine
teachablemachine.withgoogle.com/

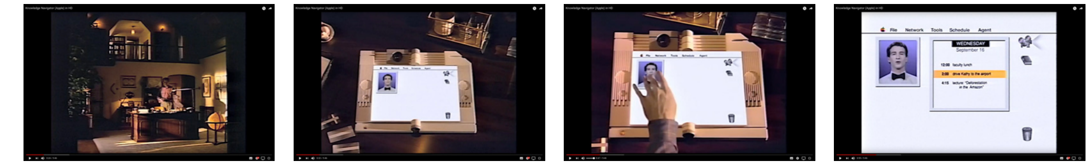
One of these AI experiments called "Teachable Machine" offers the user to teach his or her computer directly in the browser using his or her camera to have it perform an action depending on his or her gesture. The experiment makes this technology accessible to more people in a playful and fun way, potentially sparking interest for non-specialist.

2.2.1.3 Apple's Knowledge Navigator

The video documented (see fig. 23), created by Apple in 1988, envisions a professor collaborating with a colleague in 2011, using technology that didn't exist at the time but was based on capabilities that were available such as network file sharing, voice recognition, video teleconferencing.

Figure 23. Screenshots and captions of Apple's Knwoledge Navigator Video

Kevin Surace. *Knowledge Navigator (Apple) in HD*. YouTube, https://www.youtube.com/watch?v=mE2Z30pyw8c. Accessed 8 May 2018.



[Professor, named Mike enters his office]

[The Knowledge Navigator GUI and its virtual agent]
[The virtual agent speaks out the messages Mike received]

[Mike interrupts the virtual agent by touching on its visual representation]

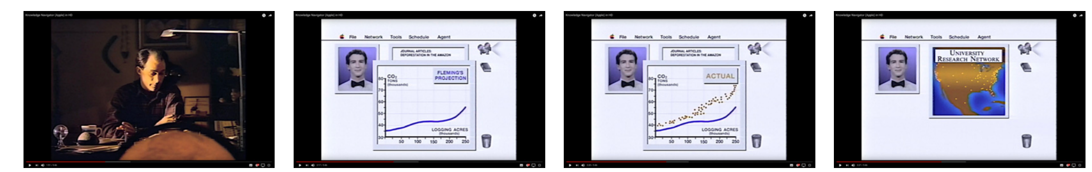
[Virtual agent speaks out Mike's schedule]
Virtual agent: "You have a lecture at 4/15 on Deforestation in the Amazon Rainforest."

Mike: "Let me see the lecture notes from last semester."

[Lecture notes are displayed on the GUI]

Mike: "No, it's not enough, I need to review more literature. Pull up all the new articles I haven't read yet."

[Virtual agent pulls out the research]
Virtual agent: "Your friend Jill Gilbert has published an article about deforestation in the Amazon and its effect on rainfall in the sub Sahara."
Mike: "Contact Jill."
Virtual agent: "I'm sorry she's not available right now I left a message that you would call."

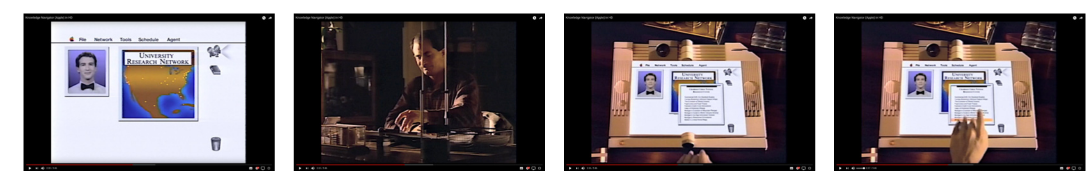


Mike: "OK. Let's see. There's an article about 5 years ago doctor Flamson or something he really disagreed with the direction of jails research."
Virtual agent: "John Fleming of absolute University, he published in the Journal of earth science of July 20 of 2006"

Mike: "He was challenging Jill's projection in the amount of carbon dioxide being released to the atmosphere through deforestation, I'd like to recheck his figures."
Virtual agent: "Here's the rate of deforestation he predicted."

Mike: "And then what happened? ... Hum. He was really off."

Mike: "Give me the University research network."
[Map of the University Research Network]

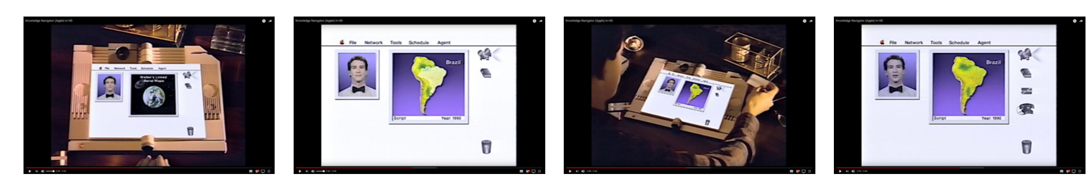


Mike: "Show only universities with geographic nodes."
[Map of the University Research Network for the universities with geographic nodes only]

[Mike interacts with the touch screen]

[Mike interacts with the touch screen]

[Mike interacts with the touch screen]

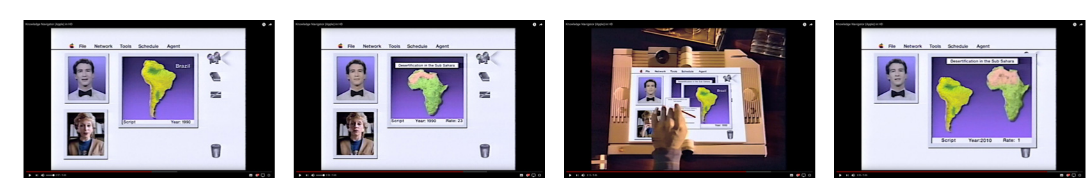


[Mike interacts with the touch screen]

Mike: "Show Brazil"
[Map of Brazil is displayed]

Mike: "Copy the last 30 years at this location at one month intervals."
[Professor inserts a magnetic card in the computer]

Virtual agent: "Excuse me Jill Gilbert is calling back".
Mike: "Great, put her through."



Jill: "Hi Mike, what's up?"
[Professor Mike and Jill have a conversation, while the virtual agent listens]

Jill: "You know I have a simulation that show the spread of the Sahara over the last 20 years. Here let me show you."
[Simulation appears on the screen and plays]

Mike: "Nice, very nice. I've got some maps of the Amazon area during the same time. Let's put these together."
[Mike interacts with the touch screen to put the maps together and plays the simulation]

Virtual agent: "While you were busy, your mother called again to remind you to pick up the birthday cake"

2.2.2 Visualization in the Context of AI and ML

2.2.2.1 Visualizing Statistical Learning Techniques and Machine Learning Models

The website R2D3 explains to the user the process behind the creation of a machine learning model to distinguish homes in New York from homes in San Francisco.

While the website introduces and defines the different steps and variables involved, it also reveals the importance of visualizations to explain how this process works but also to reveal what it means to identify patterns in data and so on.

The website goes through multiple visualizations to support the reasoning behind the creation of a machine learning model such as bar chart, scatterplot, scatterplot matrix, decision tree and so on.

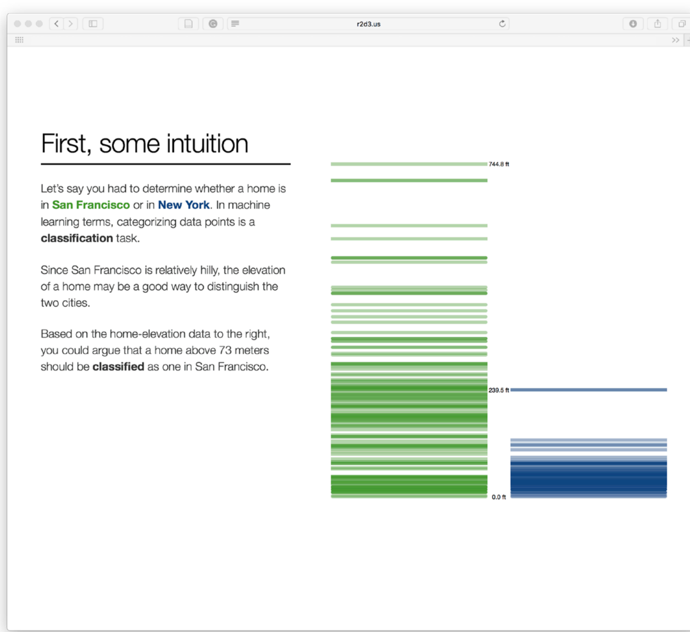


Figure 24.
Bar Chart
Categorization of the data points from home-elevation data sets of San Francisco (green) and New York (blue) in a bar chart to compare any direct trend in the data.

A Visual Introduction to Machine Learning. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/. Accessed 8 May 2018.

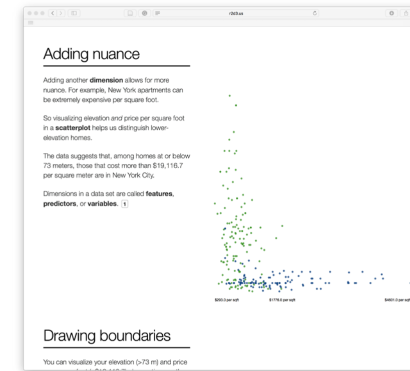


Figure 25.
Scatterplot
Visualization of the elevation and price per square foot in a scatterplot to observe correlations from the data.

A Visual Introduction to Machine Learning. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/. Accessed 8 May 2018.

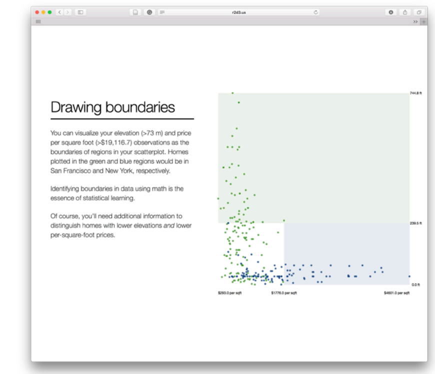


Figure 26.
Boundaries
Visualization in a scatterplot of the boundaries in the data to identify the observations from statistical learning theories.

A Visual Introduction to Machine Learning. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/. Accessed 8 May 2018.

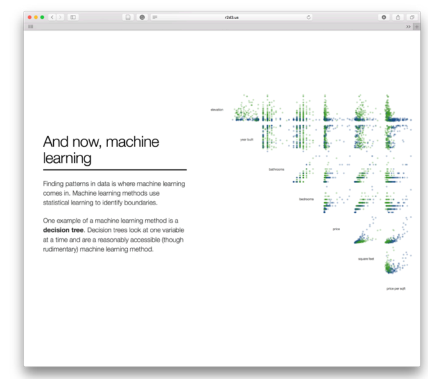


Figure 27.
Scatterplot Matrix
Visualization of the variables from the data in a scatterplot matrix to show the relationships between each pair of dimensions.

A Visual Introduction to Machine Learning. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/. Accessed 8 May 2018.

Finding patterns in data is where machine learning comes in. Machine learning methods use statistical learning to identify boundaries.

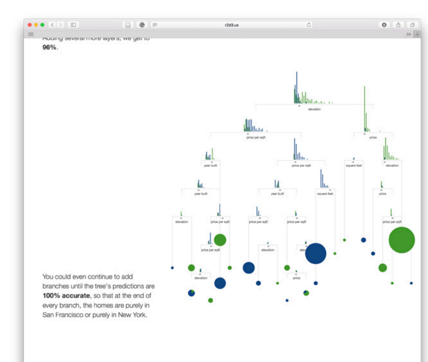


Figure 28.
Decision Tree
Decision tree as a machine learning method to identify boundaries in the data and generate a machine learning model.

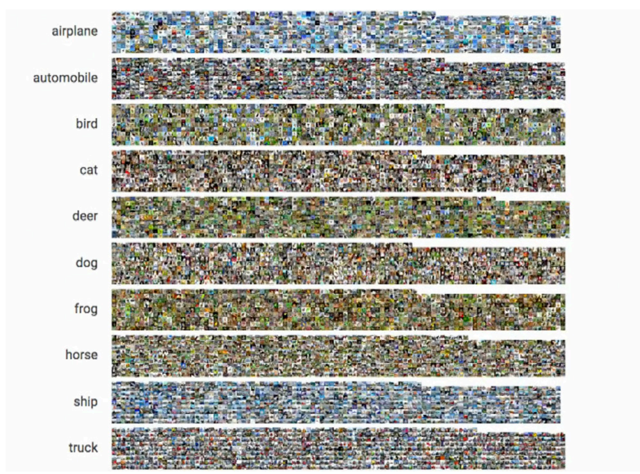
A Visual Introduction to Machine Learning. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/. Accessed 8 May 2018.

2.2.2.2 Visualizing and exploring image data sets

CIFAR-10 is a dataset containing millions of photos constituting the knowledge of a machine learning model to recognize images and their content.

Figure 29.
CIFAR-10 Dataset

Arthur M. Sackler Colloquia. *Visualization as Lingua Franca in Machine Learning - Fernanda Viegas.* YouTube, https://www.youtube.com/



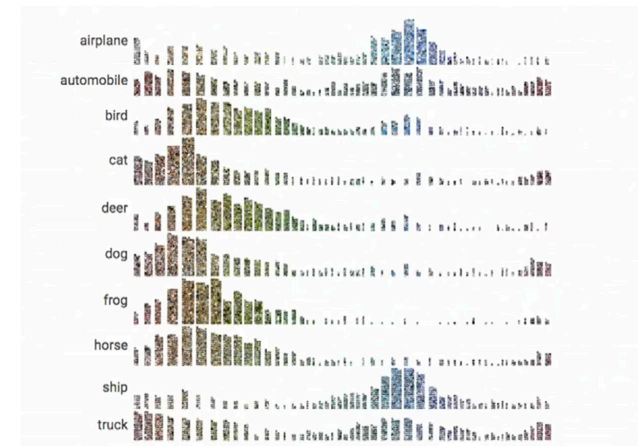
The images contained in this database are separated into classes and labeled. This classification represents the ground truth that humans are sharing about the depiction of those images.

Figure 30.
CIFAR-10 Zoom

Arthur M. Sackler Colloquia. *Visualization as Lingua Franca in Machine Learning - Fernanda Viegas.* YouTube, https://www.youtube.com/

Figure 31.
Sorting the Images by Hues

Arthur M. Sackler Colloquia. *Visualization as Lingua Franca in Machine Learning - Fernanda Viegas.* YouTube, https://www.youtube.com/

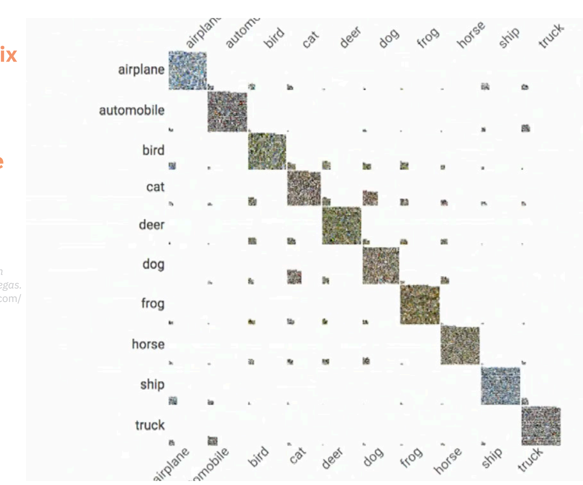


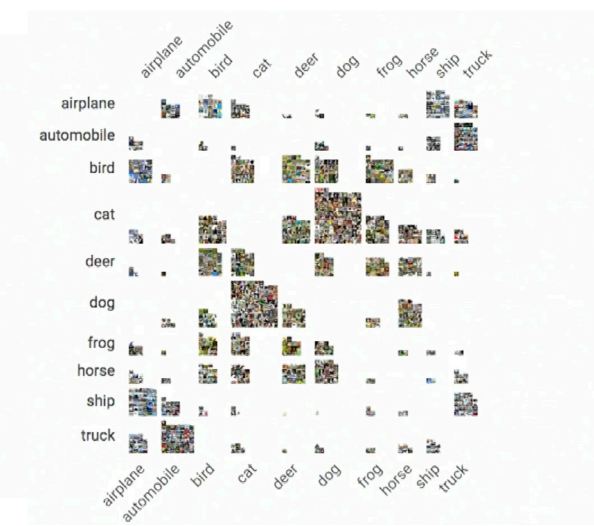
Confusion matrix is to comparing the ground truth and what the system says.

Figure 32.
Confusion Matrix
(left)

Figure 33.
Focusing on the Confusion
(right)

Arthur M. Sackler Colloquia. *Visualization as Lingua Franca in Machine Learning - Fernanda Viegas.* YouTube, https://www.youtube.com/





Population of the cells thus reveals the system accuracy to identify images. For example, the cell at the intersection of dogs and cats is highly populated showing a confusion around the differentiation between dogs and cats.

This example demonstrates how visualizations can help users see and interact with their own data in accessible and meaningful ways.

2.2.3 AI Applications

2.2.3.1 Project Dreamcatcher

Project Dreamcatcher
autodeskresearch.com/projects/dreamcatcher

Dreamcatcher, Autodesk's new generation of CAD, incorporates artificial intelligence and machine learning techniques. Dreamcatcher is a generative design system that enables designers to craft a definition of their design problem through goals and constraints. This information is used to synthesize alternative design solutions that meet the objectives. Designers are able to explore trade-offs between many alternative approaches and select design solutions to manufacture.

As stated on their website, using Dreamcatcher involves the following workflow.

Defining the design problem

The Dreamcatcher system allows designers to input specific design objectives, including functional requirements, material type, manufacturing method, problem criteria, and cost restrictions.

The designer explicitly and implicitly documents goals and constraints through a number of input modalities including natural language, image inference and CAD geometry.

Dreamcatcher has its own design knowledge base created through machine learning techniques. This knowledge base is a classified index of preexisting objects that perform with diverse functions and constraints defined in similar terms to those the user has defined in their problem definition.

Generate: shape synthesis

Loaded with design requirements, the system then searches a procedurally synthesized design space to evaluate a vast number of generated designs for satisfying the design requirements.

Explore

The resulting design alternatives are then presented back to the user, along with the performance data of each solution, in the context of the entire design solution space. Designers are able to evaluate the generated solutions in real time, returning at any point to the problem definition to adjust goals and constraints to generate new results that fit the refined definition of success.

Fabricate

Once the design space has been explored to satisfaction, the designer is able to output the design to fabrication tools or export the resulting geometry for use in other software tools.

2.2.3.2 IBM Watson for Oncology

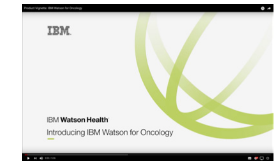
IBM Watson Health helps clinicians advance patient-centric cancer care by utilizing machine learning to identify treatments and resources that are personalized to each unique patient.

Figure 33, below, documents a demonstration of IBM Watson for Oncology. The demo showcases Watson's unique capability to analyze a patient's medical record to help identify for the clinician evidence-based and personalized treatment options.

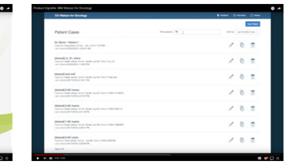
CHAPTER 2-RESEARCH × 2.2 CASE STUDIES × 2.2.3 AI APPLICATIONS

Figure 34. Screenshots and captions of IBM Watson for Oncology Demo Video

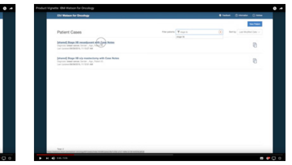
YouTube. https://www.youtube.com/watch?v=8_bi-SOXNPI. Accessed 8 May 2018.



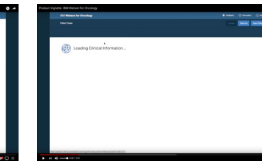
IBM Watson for Oncology



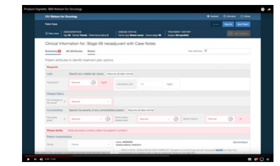
Watson for Oncology interface listing the list of patients the oncologist is going to see that day.



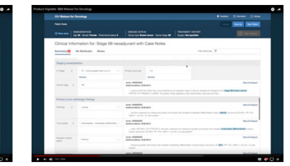
Her next appointment is with a 62 year old female with stage IIB breast cancer. She selects her from the list.



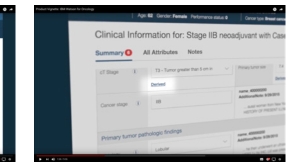
[Loading Clinical Information]
Watson analyses relevant portions of the patient's electronic medical record including her family history, notes from prior office visits, and test results.



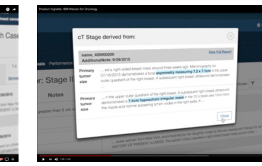
Watson summarize and highlight aspects of the patient's records and notes that are potentially significant to her cancer based on the expertise of leading oncologists.



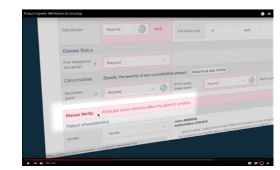
Watson also highlights required information extracted from unstructured notes within the record requiring verification and additional optional information the oncologist may choose to provide.



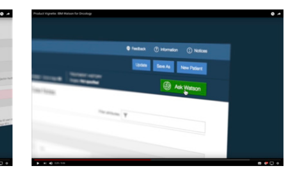
The oncologist can also find out where the information is being pulled from.
This also reveals Watson ability to understand context in a file and make inferences using Natural Language Processing regarding certain attributes utilizing information in the notes and comments in the file.



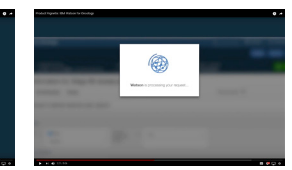
The oncologist can see the different sources of information.



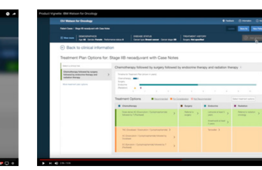
After filling out the necessary attributes, Watson will prompt the doctor to verify the information to make sure it is accurate.



Now the oncologist can ask Watson.
In seconds, Watson analyzes the case information, identifies a prioritized list of treatment options based on Memorial Sloan Kettering expertise and training, and provides links to supporting evidence.

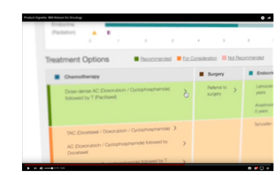


Watson draws from an impressive corpus of information, including curated literature and rationales from leading oncologists. As well as over 300 medical journals, over 200 textbooks and almost 15 millions pages of text.

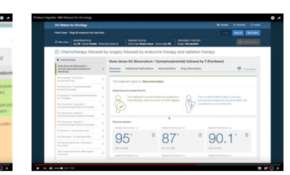


Dr. Stone now reviews the prioritized treatment plan options for her patient.

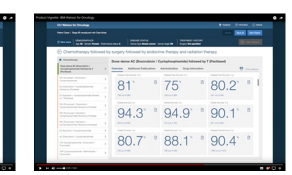
The visualized timeline is the first step in fostering collaboration between the different modalities.



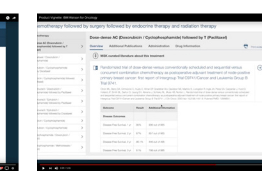
The doctor can now look at more details about this treatment plan.



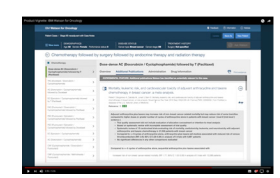
The first thing she will see is information to support the treatment option.



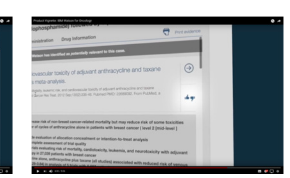
Watson is also able to extract relevant statistics from curated literature with the appropriate source information. Here the doctor can see statistics about outcomes and toxicities that have been extracted and the sources.



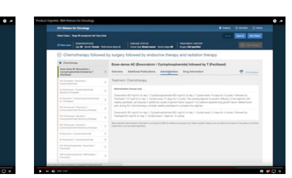
Here the doctor can see supported Memorial Sloan Kettering curated literature about this treatment option.



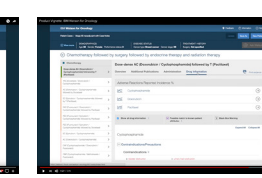
On the Additional Publications" tab, the doctor will find publications Watson has identified from its corpus that maybe relevant to both the treatment option and patient case.



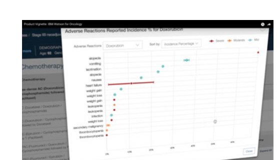
On the right, a feature that allow the doctor to provide feedback seamlessly about the publication.



On the Administration tab, Dr. Stone can view based dosing information supplied by guidelines. This information is for reference purposes only.



Finally on the drug information tab, Watson displays contraindications precautions and adverse reactions and highlights possible matches with known patient attributes.



When clicking on a specific drug, the doctor can see the associated adverse reactions reported incidence percentage.

The can finally create a report of all this information to the patient.

2.2.4 Takeaways

Visualizations appear to be critical in the context of artificial intelligence and machine learning. They can help users grasp the data by looking at the clusters of data and their content rather than looking at individual data points. Visualizations also provide ways for designers to inspect how the system is classifying the data and identify potential errors and anomalies.

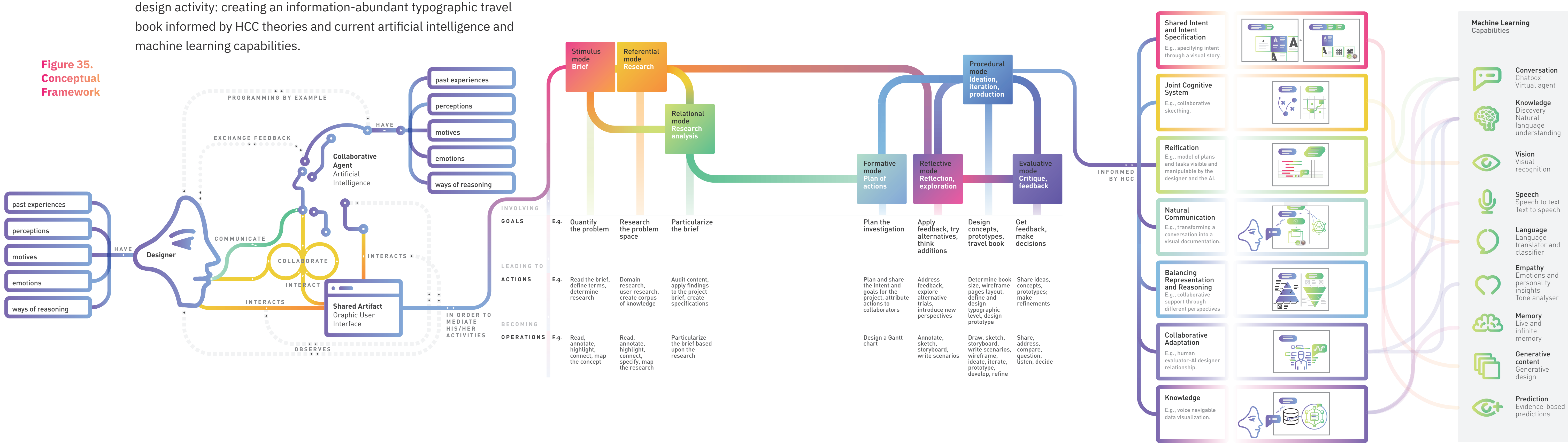
Visualizations can access the complexity of data while removing the layers of technical expertise necessary to understand the data as statisticians do. It thus allows the designer to focus on the problem by better understanding the data.

These case studies also reveal the need for more dynamic and flexible interfaces to support an intuitive exchange between the designer and the AI.

2.3 General Framework of the Investigation

The following map (see fig. 35) represents the general framework developed to address the investigation. In this map a freelance designer collaborates with an artificial intelligence system on a design activity: creating an information-abundant typographic travel book informed by HCC theories and current artificial intelligence and machine learning capabilities.

Figure 35.
Conceptual
Framework



Applied Activity Theory and Collaborative Interface Agent Paradigm

The conceptual framework below addresses how a collaborative interface agent paradigm can impact activity theory by redefining the object. In this case, the object is a collaborative interface agent defined earlier in the theory as a computer program made with algorithms, employing artificial intelligence and machine learning techniques to provide active assistance to the user (van de Gevel and Noussair 19). Artificial intelligence and machine learning capabilities suggest that both the designer and the collaborative agent will enter the situation with past experiences, perceptions, motives, emotions, and ways of reasoning.

Applied Activity Theory and Design Thinking

Together, the designer and the interface agent will collaborate to complete the travel book. Burnette's theory of design thinking and his modes of thinking inform this process.

Applied Activity Theory and Design Thinking

The collaborative interface agent helps the designer access information-abundant research gathered both from structured and unstructured data, including tailored information and knowledge of the users for whom the artifact is designed.
By enabling the designer to access meaningful and insightful data, the collaboration supports the creation of an impactful artifact.

Human-Computer Collaboration and Machine Learning Capabilities

Themes from a human-computer collaboration framework will help define the nature of the resulting collaboration between the designer and the virtual agent.

Current machine learning capabilities will inform the resulting process and collaborative work.

CHAPTER 2-RESEARCH × 2.4 MATRIX OF THE INVESTIGATION

2.4 Matrix of the Investigation

This matrix below (see fig. 36) highlights the areas of my investigation considering Burnette's Design Thinking Modes as well as the themes from the human-computer collaboration framework developed.
The matrix presents three main areas in which the interface will support the power of machine learning to:

- (1) Help designers access the value of data to improve their projects research and outcomes.
- (2) Help designers translate collaborative interactions into applicable intelligence.
- (3) Help designers integrate and synthesize knowledge into the project specifications and design making decisions.

Figure 36. Matrix of the Investigation

Chapter 3 - Interaction and Interface Design for a Human-AI Collaboration Paradigm
3.1 Accesing the Value of Data

Subquestion #1

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration, help designers access the value of data to improve their projects research and outcomes?

Machine learning is creating value about the data by:
- (1) Finding relevant information resources in the massive amount of data.
- (2) Discovering patterns in a collection of data.
- (3) Generating insights and predictions from the analysis of data.
- (4) Providing evidence for the metadata created.

As the designer engages in the design situation, intentional thoughts are expressed in answering the need and desire to manage a situation. Such a process, referring to Burnette's intentional mode (2) of design thinking, defines and establishes the ground of the design situation observed.

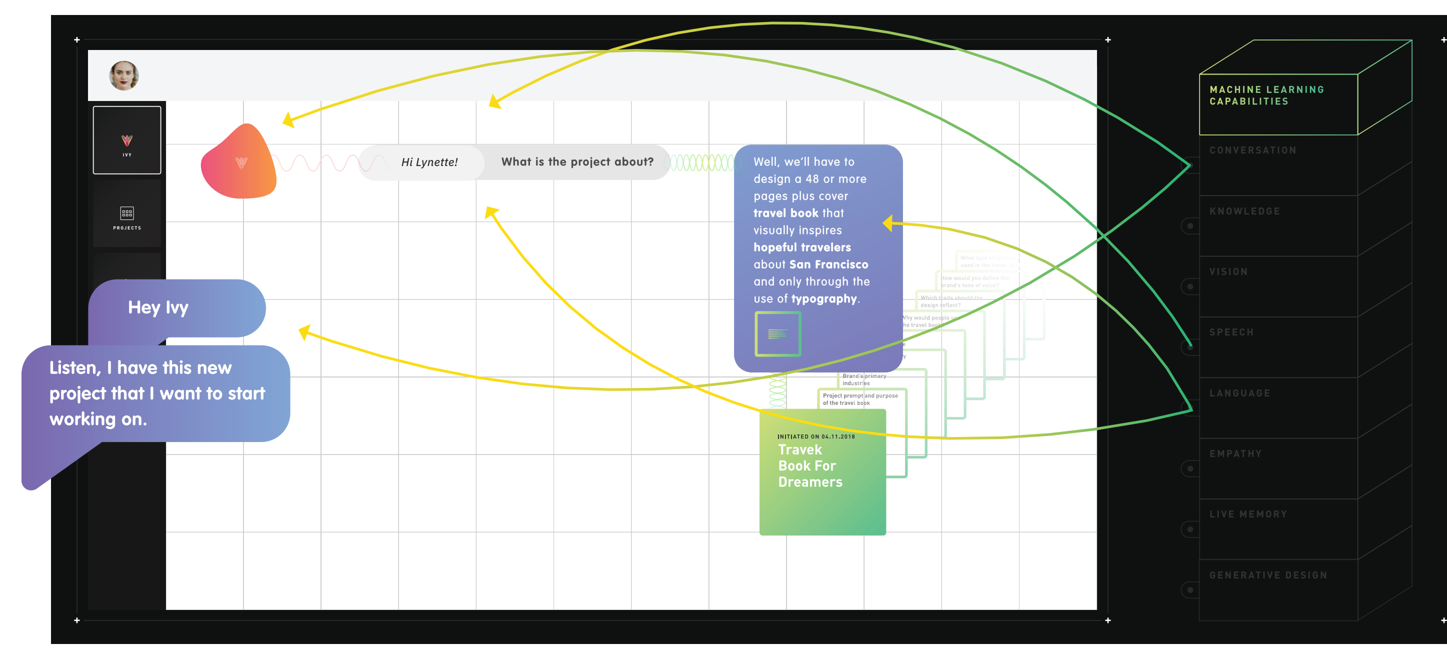
AI Wizard

In the area of interface design, a Wizard "lead[s] the user through the interface step by step to do tasks in a prescribed order" (Tidwell 55).

Wizards offer to split up tasks into a sequence of chunks, each of which can be dealt with in a discrete step by the user, simplifying the overall work. Experts often find Wizards frustratingly rigid and limiting, particularly in software supporting creative processes such as writing, art, or coding, as it encapsulates their actions in a pre-formatted box limiting the possibilities.
With ML, Wizards could tailor actions to react to the user's interactions and content. Machine learning could transform the pre-planned and restrictive interactions into personalized and helpful ones.

Scenario
In this scenario, Lynette is conversing with Ivy to start and step up a new project. Ivy is pulling references and making associations to adapt its conversation with Lynette and help to set the ground for the project.

Figure 37.
AI Wizard



Continuing with the project, nominal thoughts to identify and define discrete objects and actions that have relevance to the the situation referring to Burnette's referential mode (2) set the context of the investigation. In the design process, tools and methods such as benchmarking, content analysis and user research are particularly interesting when introducing ML capabilities.

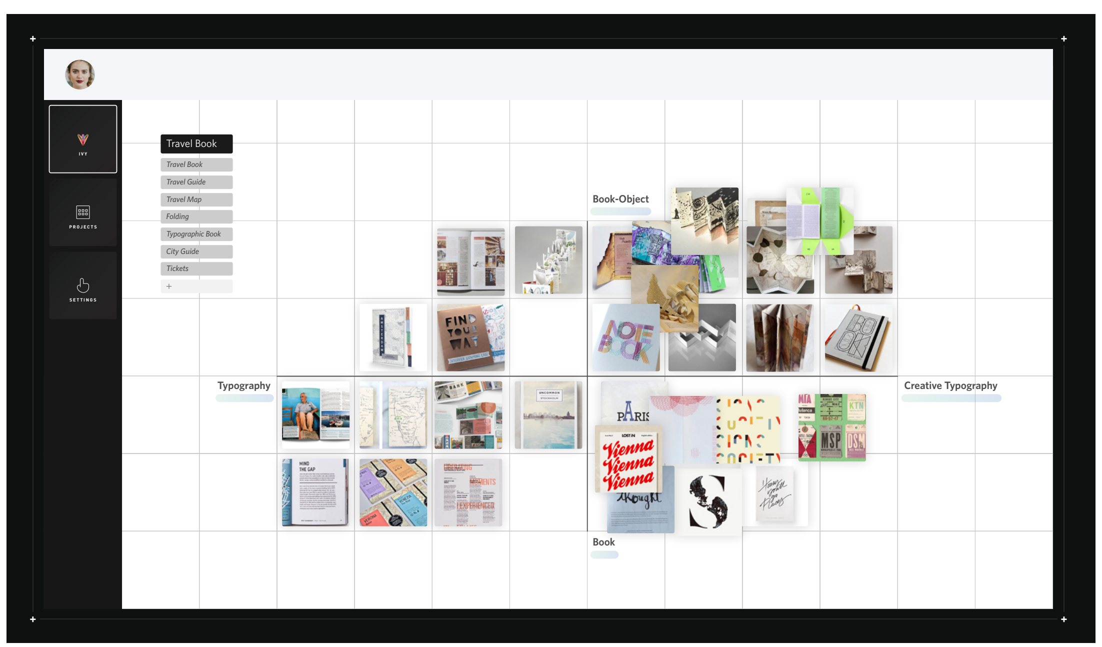
Benchmarking with AI

A benchmark is a standard or point of reference against which precedents, examples or related products may be compared or assessed. Machine learning extends benchmarking to its full potential by gathering and comparing thousands of products as well as integrating performance analysis drawn from online reviews or any data providing relevant product evaluation insights.

Scenario

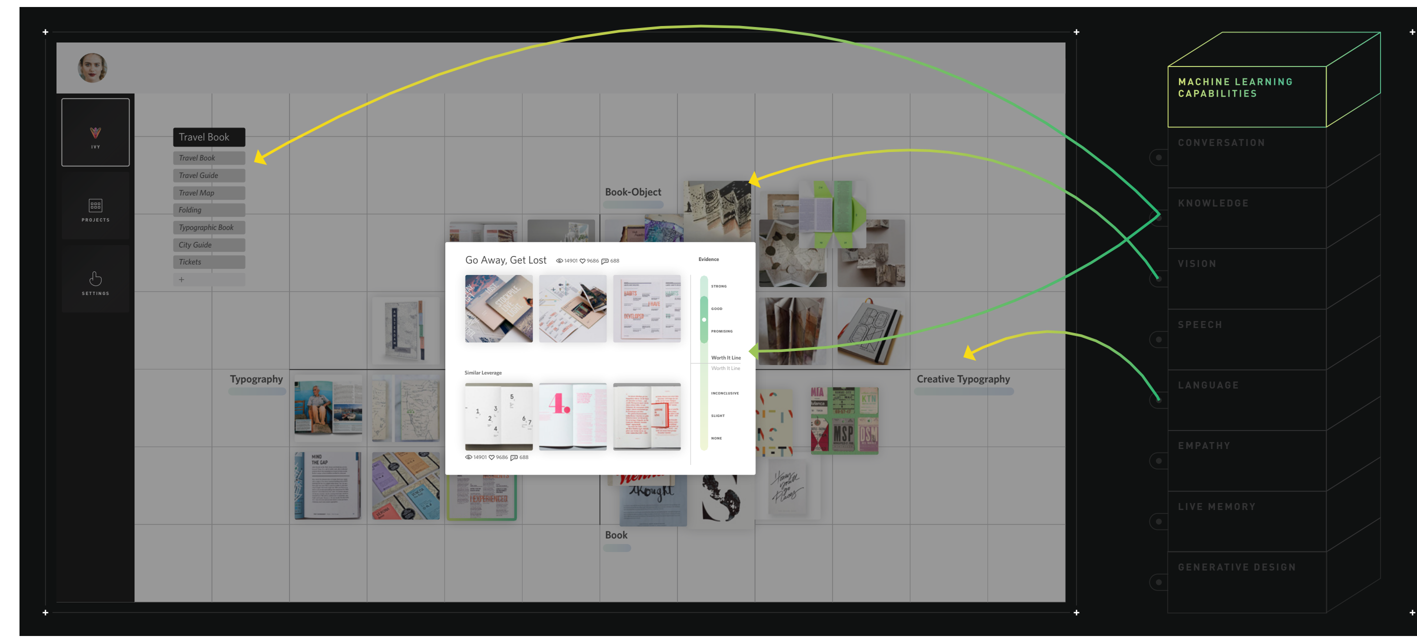
In this situation, both Lynette and Ivy are contributing to this benchmarking exercise by developing, updating, curating a matrix.

Figure 38.
Benchmarking A



By clicking on one of the project benchmarked, Lynette can access more information about the project such as additional content, relevant projects and an evidence bar chart suggesting the performance of this project regarding its relevance as a precedent.

Figure 39.
Benchmarking B



HCC and ML Considerations

Some of Ivy's capabilities here are visual recognition important to deal with that visual research associated with the benchmarking, but also language recognition to understand the labeling. There is also memory. While working on a different task, Ivy can remember the specifications of the project that are shared and understood between Lynette and Ivy.

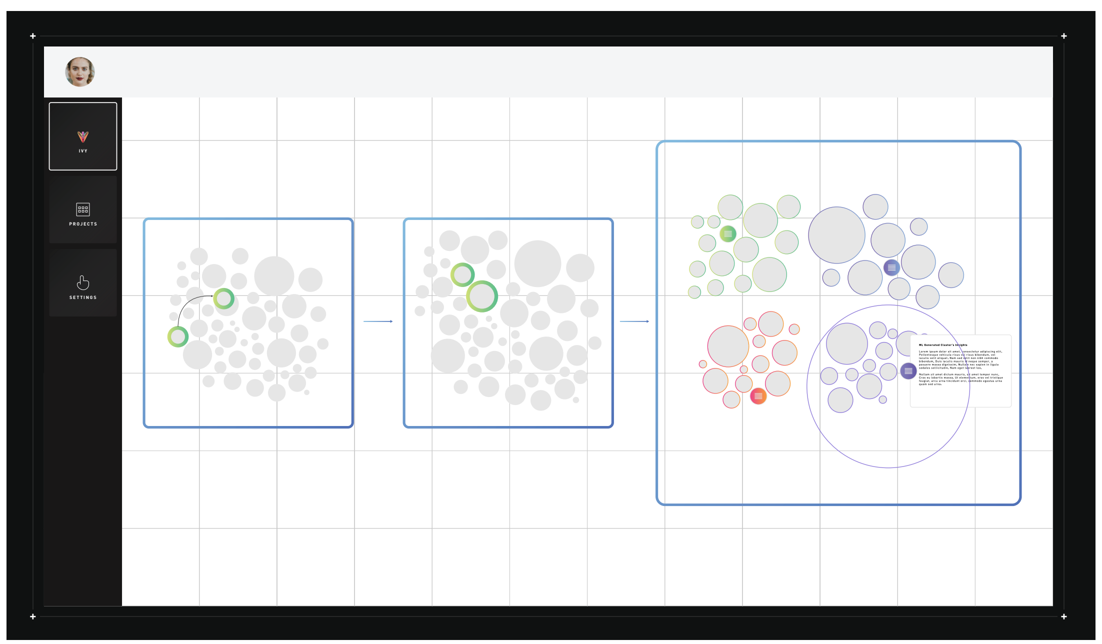
Knowledge is the basis of any collaboration, but collaborative adaptation with alternative roles of researcher/curator/evaluator is also essential according to human computer collaboration theory. And reification with the idea of visualization of a strategic way of thinking.

Affinity Diagramming

Hanington and Martin defined affinity diagramming as "a process used to externalize and meaningfully cluster observations and insights from research, keeping design teams grounded in data as they design" (21).

The inductive nature of affinity diagramming makes it particularly relevant territory for ML, which follows the same approach to data. Instead of grouping information in predefined categories, "the work is done from the bottom up, but first clustering specific, small details into groups, which then give rise to the general overarching themes" (21).

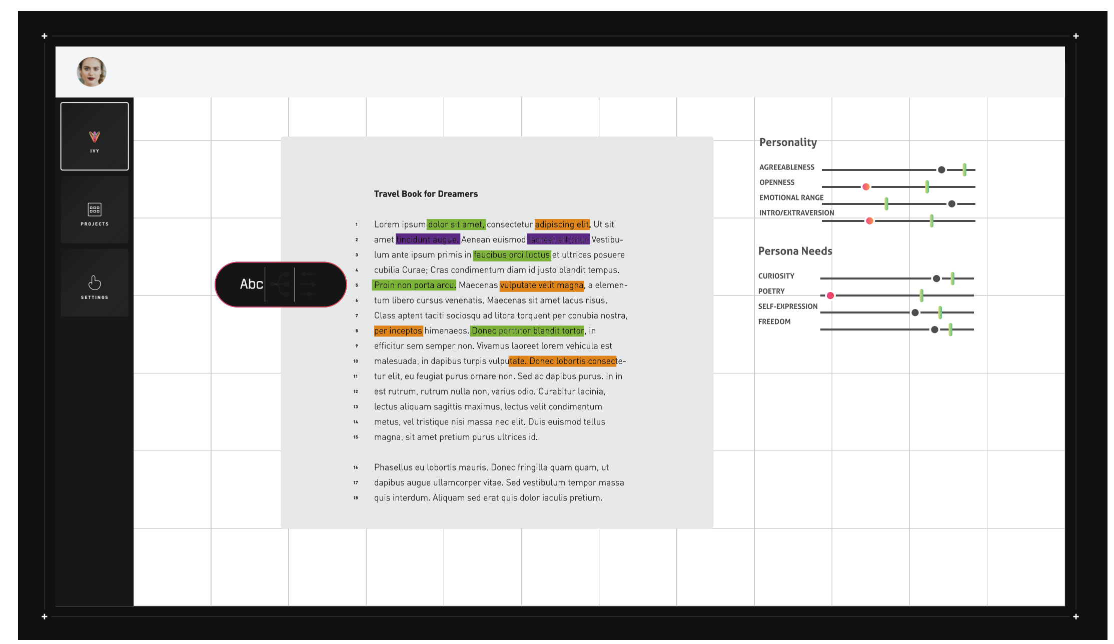
Figure 40. Affinity Diagramming



Content Analysis

Hanington and Martin defined content analysis as the "systematic description of form and content of written, spoken, or visual materials expressed in themes, patterns, and counted occurrences of words, phrases, images, or concepts" (85). Two approaches exist to content analysis: inductive and deductive. These approaches suggest the potential of collaborative adaptation between the designer and the virtual agent allowing for the creation of complementary research through different insights and perspectives.

Figure 41. Content Analysis



User Research and Persona

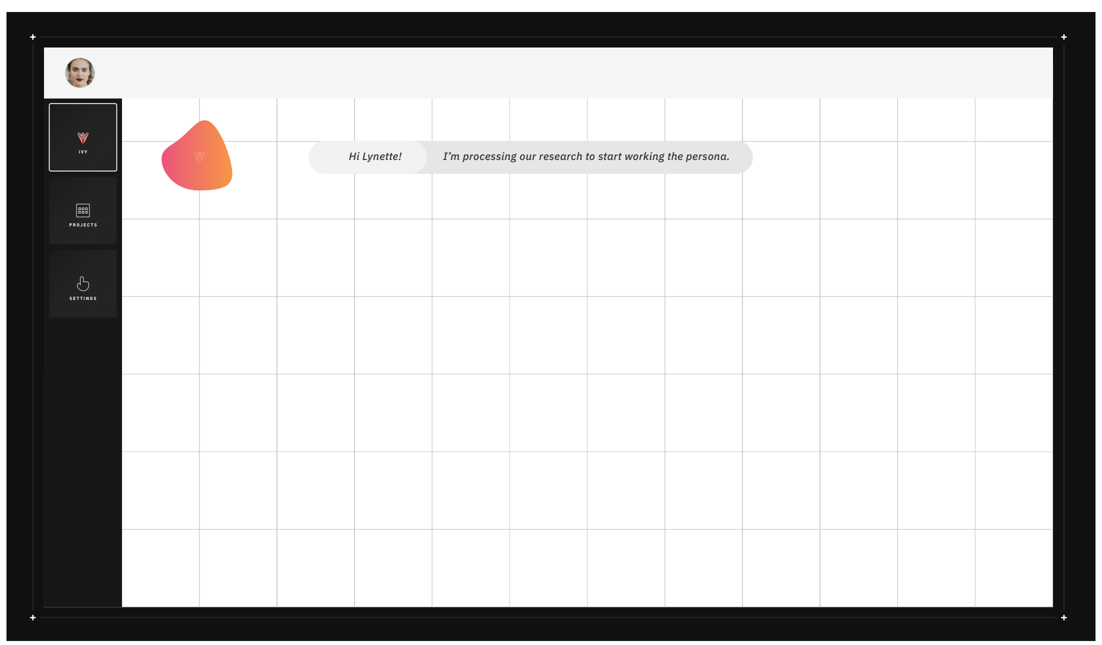
User research is critical to identify and define discrete objects and actions that have relevance to the design situation observed. Hanington and Martin defined personas as “consolidat[ing] archetypal descriptions of user behavior patterns into representative profiles, to humanize design focus, test scenarios, and aid design communication.” (Hanington and Martin 304)

Scenario

In this situation, Lynette and Ivy collaboratively make a persona.

Ivy analyzes relevant user research data gathered from a corpus of knowledge.

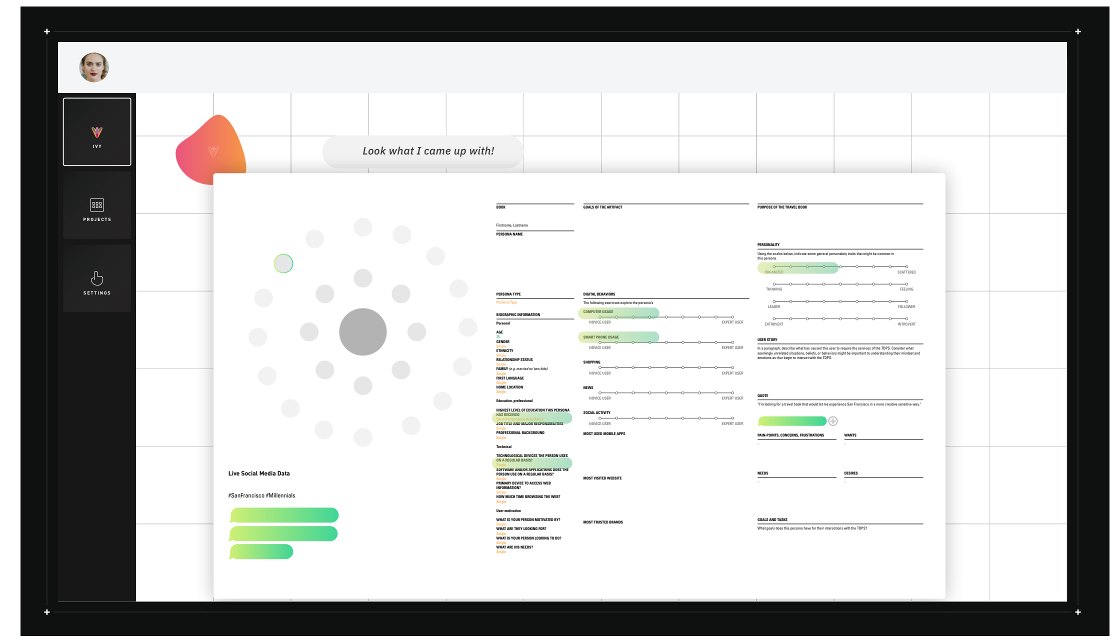
Figure 42. Persona Generation



CHAPTER 3 - INTERACTION AND INTERFACE DESIGN × 3.1 ACCESSING THE VALUE OF DATA

Ivy then summarizes the information into a dynamic persona while highlighting areas requiring input from Lynette.

Figure 43. Persona



Lynette can also update any information within the persona to particularize along the project needs and her intuitions. Lynette can interact with content such as the age of the persona. This interaction brings up a slider for Lynette to use. By changing the age range, Ivy highlights the impact of this change on the persona accordingly.

Figure 44.
Persona Slider

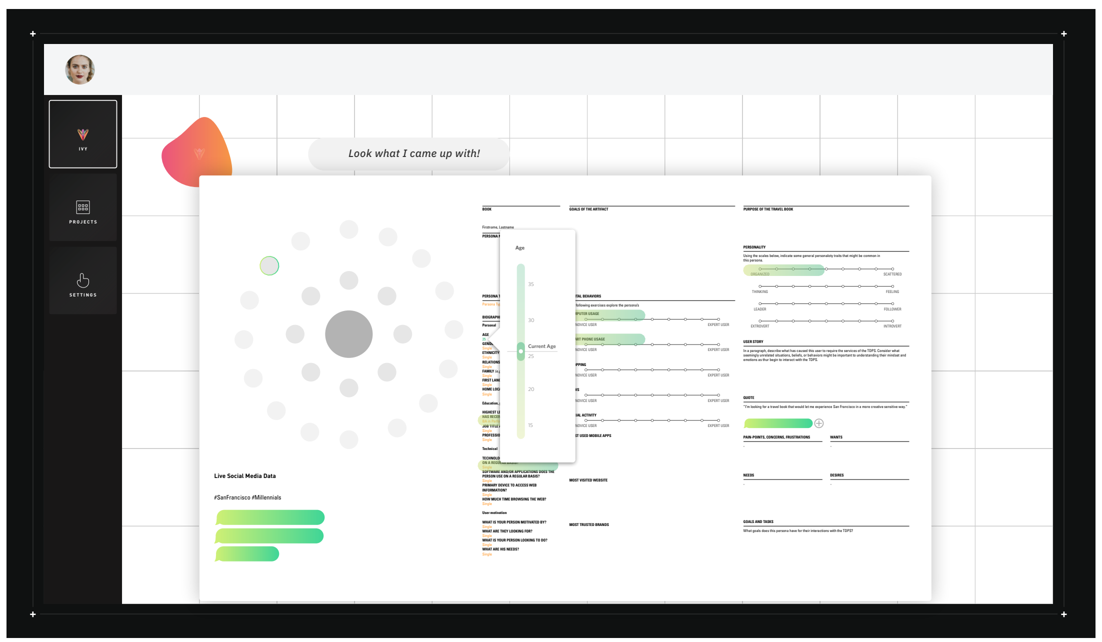
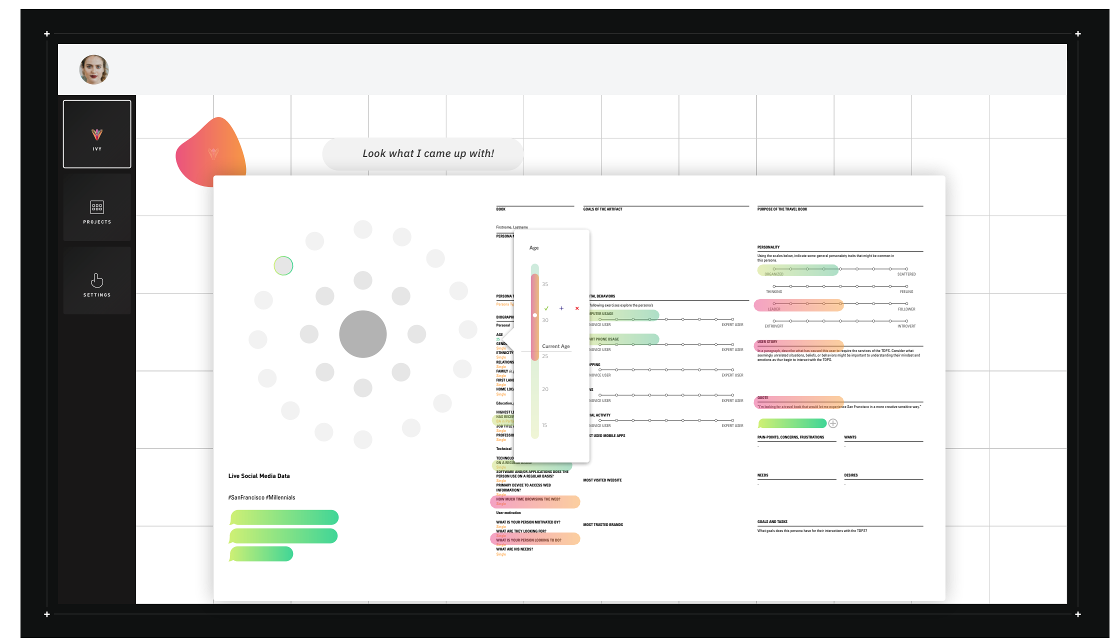


Figure 45.
Persona Slider
Impact



Conversation, knowledge, and language are the primary skills here. Empathy is also necessary when dealing with user research.

As the user persona get established, Ivy can generate an Interview Bot as well as a Persona Bot, a personification of the persona.

Lynette can then use the Interview Bot to interview potential users and generate new data to validate the users' needs and the project strategy.

The data gathered also provides a continuous update on the persona and Persona Bot, facilitating updated versions.

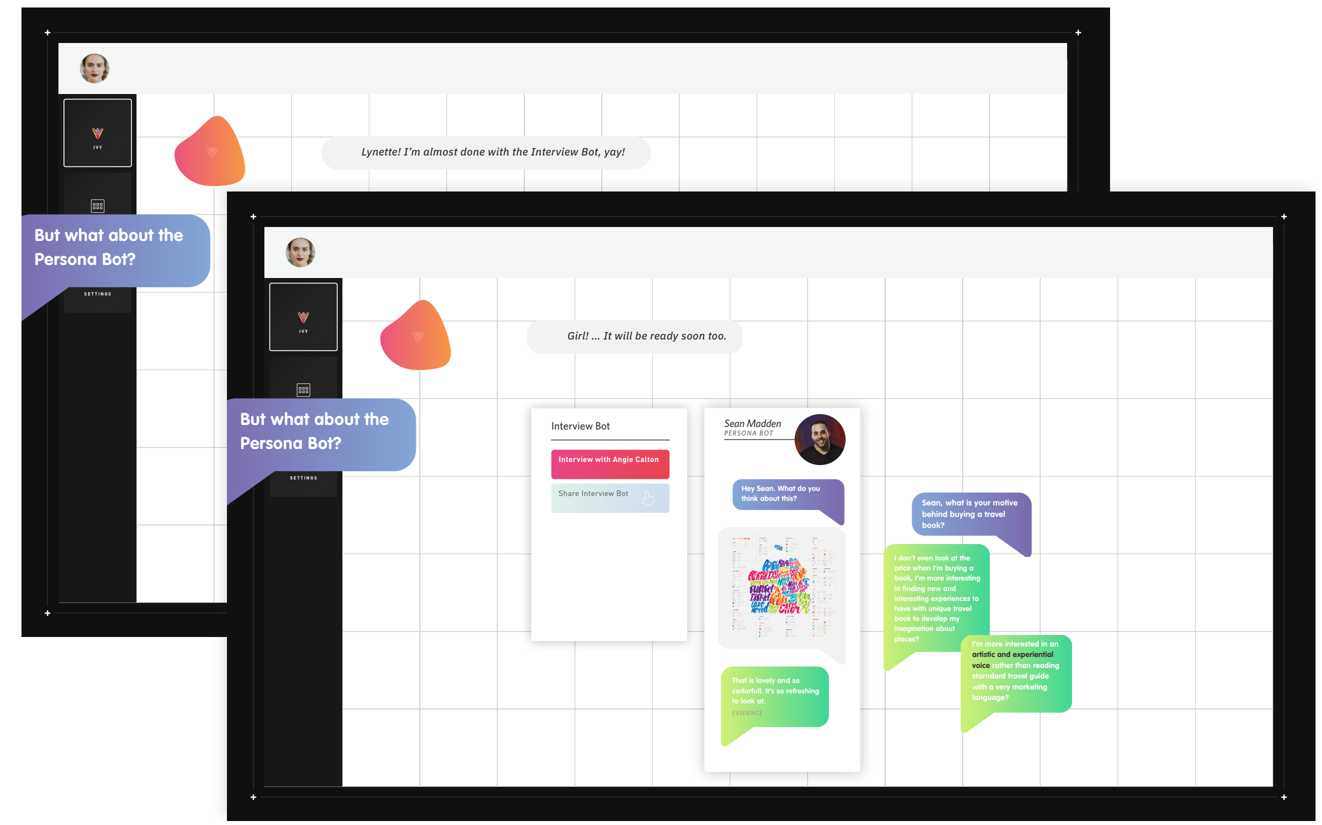
Lynette can use the Persona Bot to question Sean, the user persona. Sean and Lynette can engage in conversation significant for the project (see fig. 46).

HCC and ML Considerations

Conversation is critical when dealing with user research. Machine learning capabilities bring this conversation to the persona, making it a handy tool that tends to be descriptive but not interactive or predictive.

CHAPTER 3-INTERACTION AND INTERFACE DESIGN × 3.1 ACCESSING THE VALUE OF DATA

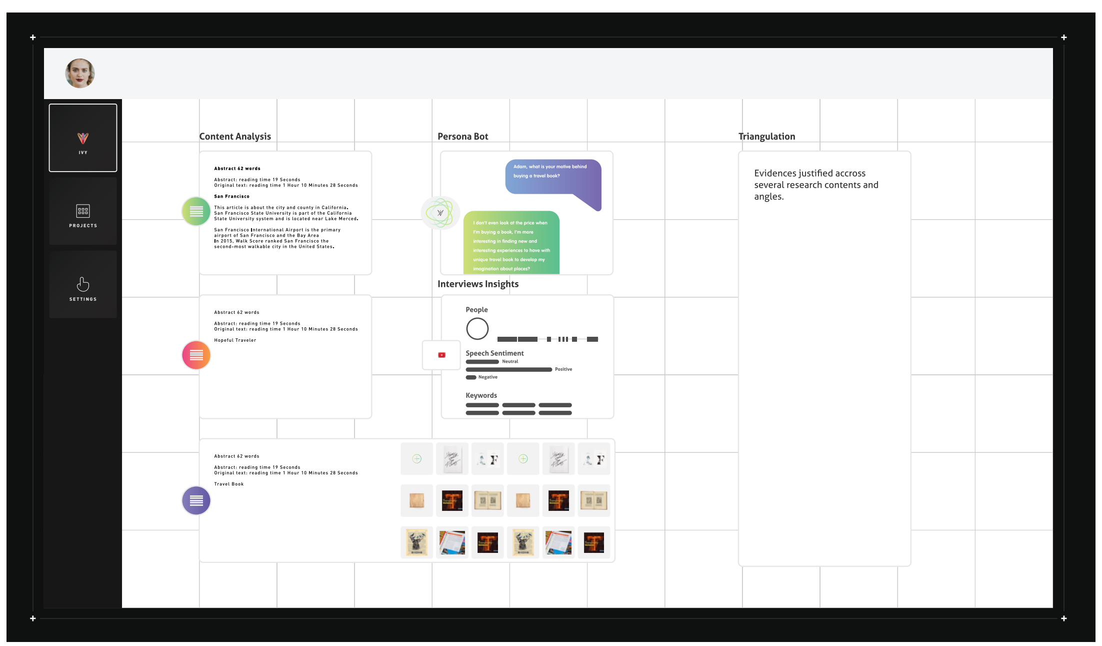
**Figure 46.
Interview Bot and
Persona Bot**



Triangulation

Once the ground and setting of the investigation are set, the designer can engage in an “associative thought to structure and analyze the referential information to fit the problematic situation and the designer’s intention regarding it” (Burnette 2). The triangulation method, defined as “the convergence of multiple methods on the same research question, to corroborate evidence from several different angles” (Hanington and Martin 401), introduces the idea of ML reasoning visibility. The method also provides the designer the means to define ways to leverage this data by creating alternative associations.

Figure 47.
Triangulation



3.2 Translating Collaborative Interactions Into Applicable Knowledge

Subquestion #2

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration, help designers translate collaborative interactions into applicable knowledge?

Knowledge is one of the required themes of human-computer collaboration. Knowledge provides a shared understanding of the situation between the designer and the virtual agent enabling successful collaboration.

This idea of knowledge is also reinforced by Burnette's formative mode of design thinking that aims at "synthesizing thought to express and communicate a plan of action, the meaning of the situation, its subject or anticipated outcome" (2).

Knowledge Map

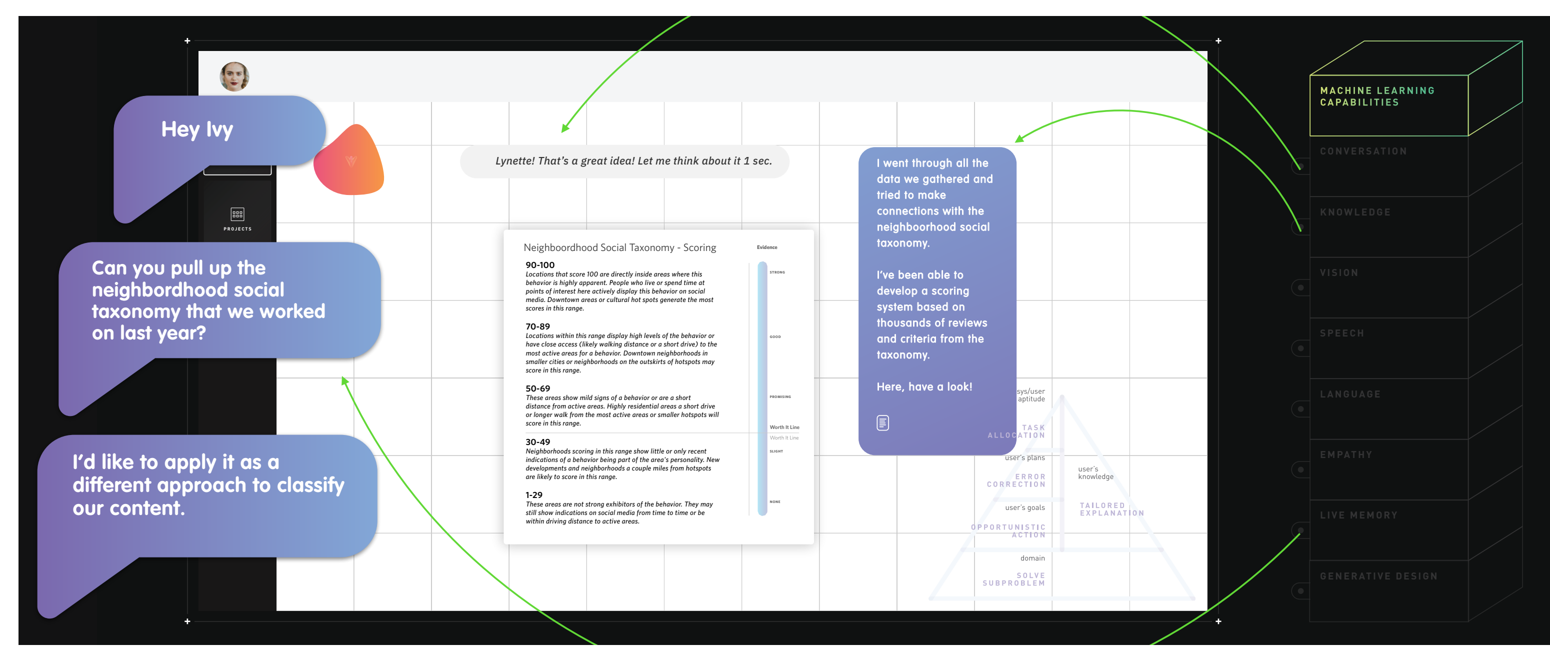
The idea of the knowledge map is represented by the idea of a concept map defined as "a sense-making tool that connects a large number of ideas, objects, and events as they relate to a certain domain. It provides a scaffolding that can help designers visualize the complexities of a system, and assists them as they make and break connections, study existing connections, and expand on what is already understood but possibly taken for granted within a particular system" (Hanington & Bella Martin 80).

This knowledge map creates a shared-knowledge space accessible and understood by both agents within the collaboration. This knowledge map also represents the fruit of the extensive collaboration between the designer and the virtual agent as the virtual agent becomes a tool to access and apply the knowledge created. The knowledge places the design process into a situation that can be comprehended, mediated and expressed.

The idea of the knowledge map also comes from the Google's Knowledge Graph.

The knowledge map provides a visual representation of shared memories, collaborative work and knowledge to transform into insightful applications.

Figure 48.
Knowledge Graph



Project Mediation

The shared knowledge established in the collaboration also contributes to the mediation taking place in this collaboration. Such mediation can occur at any moment and point of the project.

Figure 49. Project Management

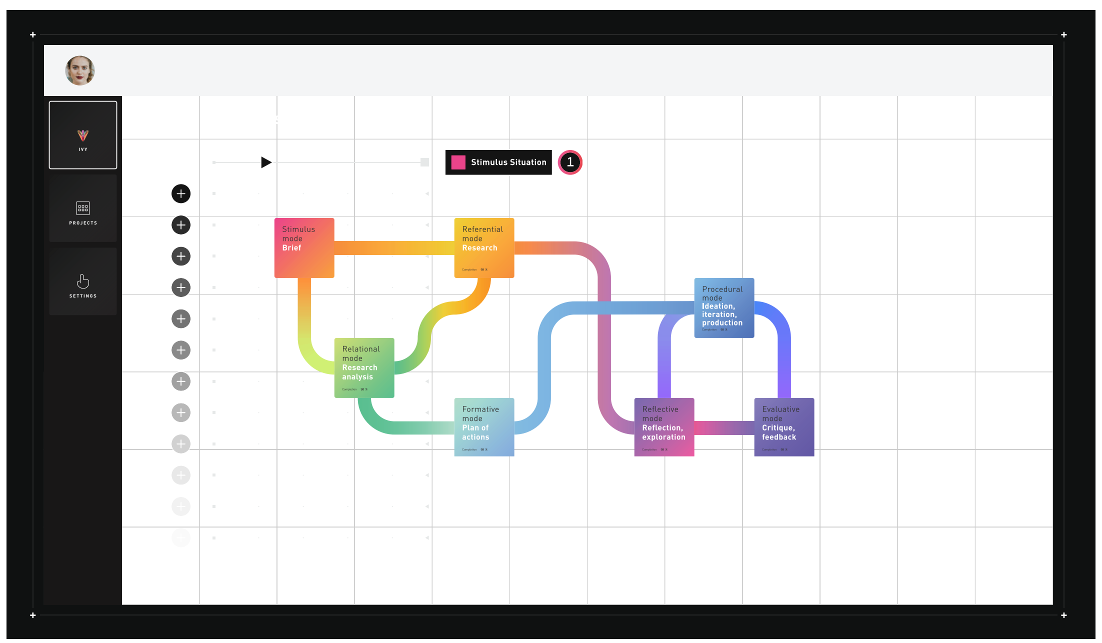
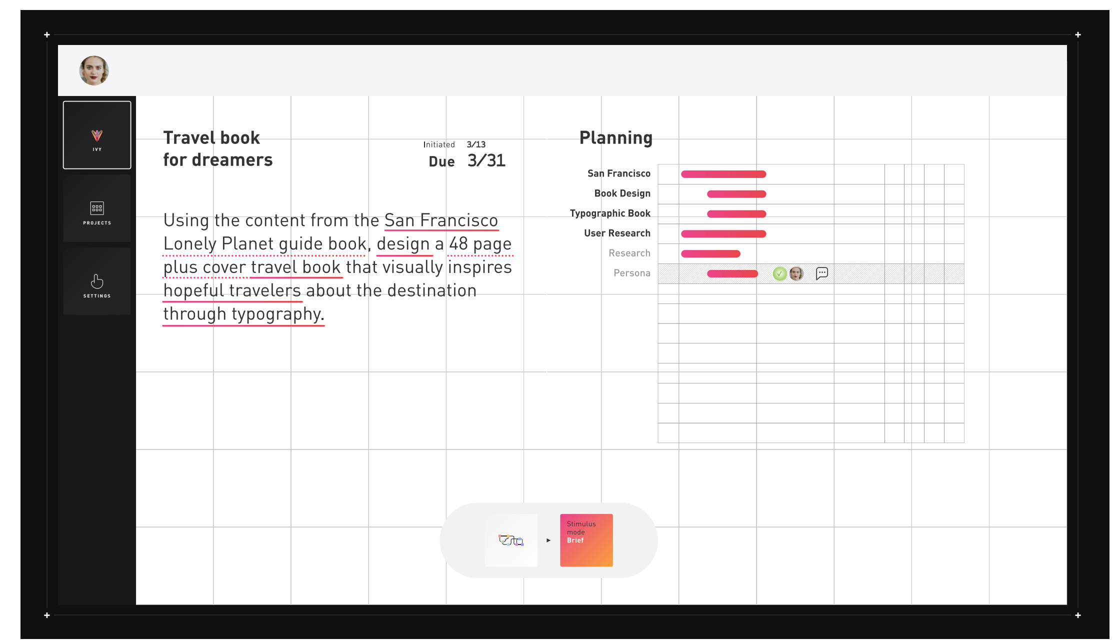


Figure 50. Project Management



3.3 Integrating and Synthesizing Knowledge

Subquestion #3

How can the design of a graphical user interface utilizing artificial intelligence and machine learning capabilities in a context of use informed by human-computer collaboration, help designers integrate and synthesize knowledge into the project specifications and design making decisions?

Informed by Burnette's relational mode, the procedural mode puts to work those thoughts to "execute sequential actions to carry out a plan or change an expression or situation" (2).

CHAPTER 3 - DESIGN × 3.3 INTEGRATING AND SYNTHESIZING KNOWLEDGE

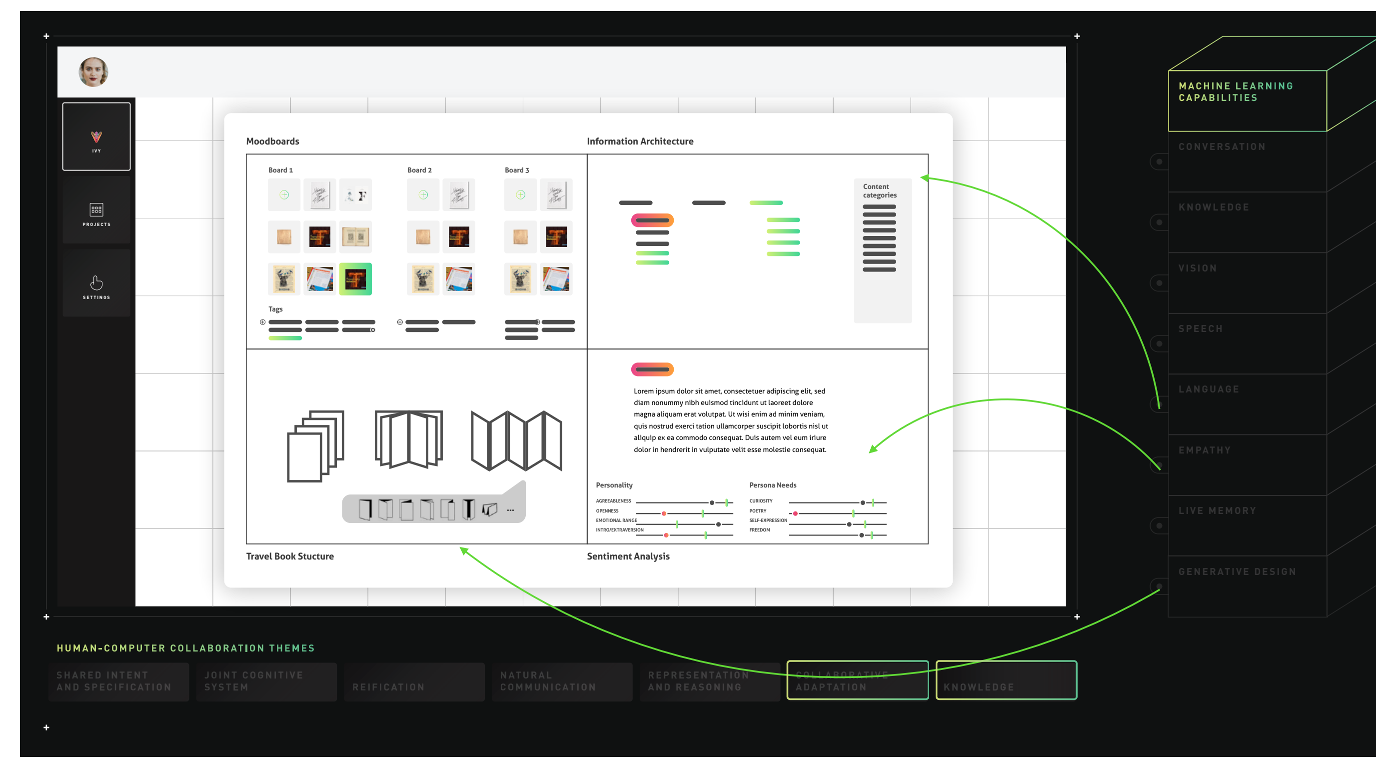
Ideation

Ideation, characterized by the creative process of generating, developing, and communicating new ideas, provides the collaborators with a method to change the situation through thoughts and actions.

Scenario
In this situation, Lynette and Ivy generate possible concepts for the project.

Capabilities in generative design, empathy, and language will be critical as we move towards more and more personalized products and services. Generative design can offer an almost infinite diversity, while sentiment analysis could help Lynette ensure that her writing is aligned with the user expectations.

Figure 51. Ideation



Design iteration and production appear to be profoundly impacted by ML capabilities as we consider the Dreamcatcher software from the case studies. Indeed, ML capabilities automate long or repetitive processes.

3.4 Takeaways

Shared Intent and Intent Specification

As in human-to-human collaboration, the notion of shared intent and intent specification is critical in a human-computer collaboration.This notion has suggested the idea of a knowledge map, as well as, the importance of mediation between Lynette and Ivy throughout the project. Both partners must share an understanding of the situation, so that the collaboration can be consistently established.

Joint Cognitive System

The notion of a joint cognitive system suggests possibilities in which the designer and the virtual agent were given, through the interface, the opportunity to utilize their respective strengths to participate in the excellent development of the project. While Ivy was able to pull up a massive quantity of data and references, the designer contributed valuable ideas—ways to solve different kinds of problems and formulate the right questions.

Reification

Reification is critical in a collaboration between a human and a virtual agent. Visual representations are the only way both partners can share an understanding of the situation, the progress, and the place in the more extensive system. Information visualization is also critical to ensure the human understands the actions of the virtual agent so that she can develop confidence and trust in the system. Finally, as ML systems are dealing with a significant amount of data, reification through data visualization appears to be necessary to create easy access to this data.

Natural Communication

Communication, either implicit or explicit, is key in any collaboration. ML gives the computer natural communication capabilities thus equalizing the relationship between the human and the computer and producing the semblance of a human-to-human collaboration. The integration of natural communication capabilities on the computer has substantial impact on the human interacting with the computer. This impact suggests the need for conversational user interface to support conversations. It also create opportunities for the creation of visual representations of those interactions.

Balancing Representation and Reasoning

Numerous data-driven design research methods involve inductive and/or deductive reasoning. Those methods provide opportunities for the designer and the virtual agent to produce in-depth collaborative research. They enables the potential for the development of various perspectives, alternatives insights, complementary approaches or a more substantial exploration.

Collaborative Adaptation

Collaborative adaptation addresses a human-computer collaboration in which the roles attributed between the designer and the virtual agent are not fixed. Such roles— endorsed by either the designer or the virtual agent—can move from designer to curator, to evaluator, to researcher, to collaborator. These roles suggest moments in which the designer learns from the virtual agent, or the virtual agent learns from the designer.

Knowledge

Knowledge, in the context of human-computer collaboration, is generated both through the data being analyzed during the design process and through the ongoing interactions between the designer and the virtual agent. The visualization of such knowledge helps both agents being aware of the situation at any instant and serves as documentation of the interactions. Such documentation is critical in design as previous experimentations and explorations often inform our work.

CHAPTER 3-DESIGN × 3.4 TAKEAWAYS

Conclusions

However, considering a virtual agent more as assistive technology in the context of AI would risk leaving human values out of the equation and thus reduce the outcomes possible through human-computer interactions. In this scenario, automation would dominate and thus negatively impact designers and their profession by shifting the act of design away from human designers.

I believe that building interfaces based on the premise that a collaboration between a user and a virtual agent is possible. In this scenario the designer and engineer must consider the human collaborator as an essential part of the system and, therefore, justify our place in the human-AI collaboration paradigm.

Nevertheless, accepting the idea of collaboration produces new problems such as the legal owner of work collaboratively made with an AI. It also generates questions around the ethics of data use regarding a system knowing about us, as groups and as individuals, more than any person on this planet—consider the recent issue with Cambridge Analytica and Facebook. Current ML systems still require humans to create and train the algorithms. This suggests the potential for bios involved in the conception of those systems. And finally, while those current systems still require the human touch, future ML learning systems will build other ML systems that communicate and train each other without any humans involved.

While much more research needs to be done to fully understand the scope of artificial intelligence and machine learning applications used in the design practice, my research in human-computer collaboration showed the potential of addressing this idea of partnership to create a framework that will propose considerations to building systems and interfaces that will preserve human value in the loop of those transformations.

BIBLIOGRAPHY

Bibliography

Alpaydin, Ethem. *Machine Learning: The New AI*. The MIT Press, 2016.

Armstrong, Helen, editor. *Digital Design Theory: Readings from the Field*. Princeton Architectural Press, 2016.

Armstrong, Helen. *Digital Design Theory: Readings from the Field*. Princeton Architectural Press, 2016.

Armstrong, Helen. *Graphic Design Theory: Readings from the Field*. 1 edition, Princeton Architectural Press, 2009.

ben, Ben Shneiderman. *Supporting Creativity with Advanced Information-Abundant User Interfaces*. p. 15.

BI Search and Text Analytics: New Additions to the BI Technology Stack. http://www.bi-bestpractices.com/view-articles/5643. Accessed 8 May 2018.

Burnette, Charles H. *A Theory of Design Thinking*. *www.academia.edu*, https://www.academia.edu/209385/A_Theory_of_Design_Thinking. Accessed 8 May 2018.

Burnette, Charles H. *Viewpoint: The Role of Artificial Intelligence in Design Thinking*. *www.academia.edu*, https://www.academia.edu/35274654/Viewpoint_The_Role_of_Artificial_Intelligence_in_Design_Thinking. Accessed 8 May 2018.

Calistri-Yeh, Randall J. *Knowledge Requirements for Human-Computer Collaboration*. p. 5.

Campbell, Murray, et al. "Deep Blue." *Artif. Intell.*, vol. 134, no. 1–2, Jan. 2002, pp. 57–83. *ACM Digital Library*, doi:10.1016/S0004-3702(01)00129-1.

Cheung, and Ada Hoi-Fay. *A Collaborative Interface Agent for Lotus ESuite Mail*. Jan. 1998.

Clark, Jack. *Artificial Intelligence: Teaching Machines to Think Like People*. https://www.oreilly.com/data/free/artificial-intelligence.csp. Accessed 8 May 2018.

"Computers and Creativity Support: Knowledge, Visualisation and Collaboration." *Knowledge-Based Systems*, vol. 10, no. 1, June 1997, pp. 3–13. *www.sciencedirect.com*, doi:10.1016/S0950-7051(97)00008-7.

Crouser, R. J., and R. Chang. "An Affordance-Based Framework for Human Computation and Human-Computer Collaboration." *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, Dec. 2012, pp. 2859–68. *Crossref*, doi:10.1109/TVCG.2012.195.

Davis, Meredith. *Graphic Design Theory*. 1 edition, Thames & Hudson, 2012.

Frey, Carl Benedikt, and Michael A. Osborne. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, vol. 114, Jan. 2017, pp. 254–80. *Crossref*, doi:10.1016/j.techfore.2016.08.019.

Goodrich, Michael A., and Alan C. Schultz. "Human-Robot Interaction: A Survey." *Foundations and Trends® in Human-Computer Interaction*, vol. 1, no. 3, 2007, pp. 203–75. *Crossref*, doi:10.1561/1100000005.

"Google Cloud Machine Learning at Scale." *Google Cloud*, https://cloud.google.com/products/machine-learning/. Accessed 8 May 2018.

Green, Scott A., et al. “Human-Robot Collaboration: A Literature Review and Augmented Reality Approach in Design.” *International Journal of Advanced Robotic Systems*, vol. 5, no. 1, Mar. 2008, p. 1. *Crossref*, doi:10.5772/5664.

Guszcza, James, et al. *Why Humans and Computers Think Better Together*. p. 24.

Harwood, John. *The Interface: IBM and the Transformation of Corporate Design, 1945–1976*. 1 edition, Univ Of Minnesota Press, 2011.

Hebron, Patrick. *Machine Learning for Designers - O’Reilly Media*. https://www.oreilly.com/design/free/machine-learning-for-designers.csp. Accessed 8 May 2018.

Hillis, Danny. “The Enlightenment Is Dead, Long Live the Entanglement.” *Journal of Design and Science*, Feb. 2016. *jods.mitpress.mit.edu*, doi:10.21428/1a042043.

IBM Watson. https://www.ibm.com/watson/?S_PKG=AW&cm_mmc=Search_Google-_-Consolidated+Advertising_Pillars-_-NA_US-_-ibm+watson_Exact_AW&cm_mmca1=000027HR&cm_mmca2=10006704&mkwid=4f0fbbdb-1425-4991-8061-67d9b75b5787%7C447%7C104673&cvosrc=ppc.google.ibm%20watson&cvo_campaign=000027HR&cvo_crid=258980041325&Matchtype=e&cm_mmca7=1021278&cm_mmca8=kwd-2846208261&cm_mmca9=4f0fbbdb-1425-4991-8061-67d9b75b5787&cm_mmca10=258980041325&cm_mmca11=e. Accessed 8 May 2018.

Kuutti, Kari. *Context and Consciousness*. Edited by Bonnie A. Nardi, Massachusetts Institute of Technology, 1995, pp. 17–44. *ACM Digital Library*, http://dl.acm.org/citation.cfm?id=223826.223828.

Kvan, Thomas. “Collaborative Design: What Is It?” *Automation in Construction*, vol. 9, July 2000, pp. 409–15. *ResearchGate*, doi:10.1016/S0926-5805(99)00025-4.

Lemke, Andreas C., and Gerhard Fischer. “A Cooperative Problem Solving System for User Interface Design.” *Proceedings of AAAI-90, Ninth National Conference on Artificial Intelligence*, 1990, pp. 479–484.

Lesh, Neal, et al. “Using Plan Recognition in Human-Computer Collaboration.” *UM99 User Modeling*, edited by Judy Kay, vol. 407, Springer Vienna, 1999, pp. 23–32. *Crossref*, doi:10.1007/978-3-7091-2490-1_3.

Nardi, Bonnie A. *Context and Consciousness*. Edited by Bonnie A. Nardi, Massachusetts Institute of Technology, 1995, pp. 7–16. *ACM Digital Library*, http://dl.acm.org/citation.cfm?id=223826.223827.

“Overview of Human-Computer Collaboration.” *Knowledge-Based Systems*, vol. 8, no. 2–3, Apr. 1995, pp. 67–81. *www.sciencedirect.com*, doi:10.1016/0950-7051(95)98369-H.

Rich, Charles, and Candace L. Sidner. “Segmented Interaction History in a Collaborative Interface Agent.” *Proceedings of the 2Nd International Conference on Intelligent User Interfaces*, ACM, 1997, pp. 23–30. *ACM Digital Library*, doi:10.1145/238218.238222.

Shanahan, Murray. *The Technological Singularity*. 1 edition, The MIT Press, 2015.

Shneiderman, Ben. “Supporting Creativity with Advanced Information-Abundant User Interfaces.” *Frontiers of Human-Centered Computing, Online Communities and Virtual Environments*, Springer, London, 2001, pp. 469–80. *link.springer.com*, doi:10.1007/978-1-4471-0259-5_34.

Silverman, Barry. “Human-Computer Collaboration.” *Human-Computer Interaction*, vol. 7, June 1992, pp. 165–96. *DataCite*, doi:10.1207/s15327051hci0702_2.

Stolterman, Erik. *Perspective The Nature of Design Practice and Implications for Interaction Design Research*.

Tidwell, Jenifer. *Designing Interfaces*. p. 577.